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Can Oil Price Predict Exchange Rate? Empirical Evidence from Deep Learning

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ABSTRACT

This paper critically analyses the predictability of exchange rates using oil prices. Extant literature that investigates the significance of oil prices in forecasting exchange rates remains largely inconclusive due to limitations arising from methodological issues. As such, this study uses deep learning approaches such as Multi-Layer Perceptron, Convolution Neural Network (CNN), and Long Short-Term Memory to predict exchange rates. In addition, the Empirical Mode Decomposition (EMD) of time series dataset was utilized to ascertain its effect on the quality of prediction. To examine the efficacy of using oil prices in forecasting exchange rates, bivariate models were also built. Of the three bivariate models developed, the EMD-CNN model has the best predictive performance. Results obtained show that oil price information has a strong influence on forecasting exchange rates.

Keywords: Exchange rate, Oil prices, Deep learning, Convolution neural network, Multilayer perceptron, Long short-term memory
JEL Classifications: Q43, C61, E17

1. INTRODUCTION

The importance of crude oil in the global economy has prompted studies on its financial and economic implications. As a result of oil shocks in the 1970s, economists and policymakers have continued to be concerned about the price of crude oil and its macroeconomic consequences. For instance, the path-breaking findings by Hamilton (1983), which argued that oil price is a factor contributing to recessions in the United States has paved the way for similar research by scholars see e.g. (Filis and Chatziantoniou, 2014; Herrera et al., 2011; Salisu et al., 2017). Among the macroeconomic variables at the receiving end of an oil price shock, the exchange rate is seen as the principal conduit through which variations in oil prices transacted in US currency is conveyed to financial and real markets. The reason for this is that a rise in oil prices affects a country's wealth since it causes the transfer of revenue from nations importing oil to those exporting nations as a result of change in trading conditions. However, exchange rates and the balance of trade are also projected to shift (Abed et al., 2016; Reboredo, 2012).

Like other financial variables, the exchange rate is characterized by uncertainties thus making the forecast of its parameters highly unpredictable. In the financial sector, accurate predictions of important variables, such as the exchange rate, have a huge influence on the global market and domestic economic policy formulation. The assessment of purchasing power of different currencies by both governments and businesses is made based on movement in exchange rates, as such, meaningful investment and trading strategy necessitates accurate exchange rate modeling and forecasting (Baghestani and Toledo, 2019). In addition to the highly uncertain nature of exchange rates, their movement is driven

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by socio-economic, political, and psychological behavior of traders and investors as well as oil price movement. In existing studies, oil price has been identified as a key indicator of exchange rate fluctuation because oil price is almost 100% indexed in US dollars (Bal and Rath, 2015). As a result, there are exchange rate concerns between domestic currencies and the US dollar for nations participating in the crude oil business. This further amplifies the association that exists between oil prices and exchange rates (Reboredo and Rivera-Castro, 2013). Another important factor that further strengthens the interaction between exchange rates and oil prices is the globalization and financialization of the market for crude oil. As a result, portfolio managers and investors are increasingly including crude oil in currency portfolios that further serve to reinforce the co-movement between the two variables (Ma et al., 2019; Salisu and Mobolaji, 2013). However, empirical findings on linkages between exchange rates and oil prices are eclectic and not conclusive. While explorations, such as those by Chen and Chen (2007); Tiwari et al., (2013); Benhmad (2012); and Lizardo and Mollick (2010) discovered that changes in oil prices cause fluctuations in exchange rates, others by Reboredo (2012) and Sadorsky (2000) demonstrated that changes in exchange rates may have an effect on oil prices. Under these circumstances, the currency of a small open economy like that of Nigeria, which is active in crude oil trade and connected to the global market, is expected to be susceptible to crude oil trade fluctuations.

In the literature, several econometric tools ranging from Vector Autoregression, Structural Vector Autoregression, quantile regression etc., have been applied to the challenge of predicting exchange rates and oil prices. These studies include Akbar et al. (2019); Amano and Van Norden (1998); Reboredo (2012); Chen et al. (2016); Chen and Chen (2007); Jiang et al. (2020); Kisswani et al. (2019); Lizardo and Mollick (2010); and Nusair and Olson (2019). Similar analytical approaches were employed in Nigerian empirical works on the connection between oil prices and exchange rates (Asaleye [2019]; Lawal et al., [2016]; Manasseh [2019]; Okonkwo and Mojekwu [2018]; Salisu and Mobolaji [2013] among others). Although these approaches have gained a wide audience in the empirical literature, they are only applicable in dealing with linear problems with normal distribution variables. Artificial intelligence (AI) models, such as artificial neural networks (ANNs), deep learning (DL), support vector regression (SVR), and Bayesian neural networks (BNNs) have shown to be effective in overcoming these limitations.

A widely held belief in the area of AI is that in the future, machines will increasingly behave and think like humans. Expert systems, fuzzy expert systems, deep and ANN systems, neuro-fuzzy logic systems, and knowledge-based systems are all components of AI (Singh and Sagar, 2013). Machine learning is an application of AI technology that allows machines to learn and improve without the help of humans. Recently, machine learning has transformed several fields of research, from medicine (Aliyu et al., 2021), image recognition (Krizhevsky et al., 2012), and machine translation (Wu et al., 2016) to intertemporal optimization (Borges et al., 2021). These discoveries were made possible by significant advancements in computer hardware, software, and methodologies. The exponential growth of data generation and the need to find optimal solutions to difficult problems have led to increasingly more intelligent algorithms being explored. For instance, the development of bio-inspired algorithms such as genetic algorithms, particle swarm optimization, whale optimization, ant colony optimization, artificial bee colony, dragonfly, cuckoo search, firefly, bat optimization algorithms, and artificial plant optimization algorithms, have increased the scope of the application of AI in bio-computing and forecasting (Kar, 2016). Another important area of AI that has recently gained prominence is swarm intelligence (SI), which is a concept inspired by biological systems that mimic the collaborative behavior of a group of animals as they compete for survival (Chakraborty and Kar, 2017).

AI is revolutionizing business, corporate practices, government policy, the economy, and society by transforming stakeholder and citizen experiences and interactions. In line with this, Loureiro et al., (2021) present an overview of AI in the business environment and recommend a research plan for the future. Similarly, Goralski and Tan (2020) analyzed the effects of AI on sustainable development with a special emphasis on the progress of the UN's Sustainable Development Goals, combining the views of business strategy and public policy. In recent times, AI models have been utilized to predict the relationship between financial variables (Safi et al., [2022]; Chen et al., [2021]; Cogoljević et al., [2018]; Wang et al., [2020]; Rybinski [2020]; Wu et al., [2020]) and the spread of COVID-19 (Safi and Sanusi [2021]; Vaishya et al., [2020]; Pham et al.,[2020]). These AI techniques enable the identification of hidden, innovative trends and remarkable information in massive datasets with no need for prior understanding of the data. Also, several studies employ historical data to forecast future outcomes depending on exchange rate characteristics, thus establishing the mechanism through which exchange rate movement is affected, or is influenced by, variations in other economic indices. In this light, this article investigates the influence of other economic variables such as oil prices in predicting exchange rates.

Interestingly, when reviewing previous works on the oil price and exchange rate nexus, we clearly note a dearth of research that accesses the linkage between them using these approaches. This article is structured into six sections to achieve the stated objective. Section 2 provides a literature review. Section 3 discusses the methods employed and Sections 4 and 5 explain the experiments and results obtained, while Section 6 highlights the policy implications and conclusions.

2. LITERATURE REVIEW

Over the past few decades, research on exchange rate forecasting has advanced from two major perspectives. The first refers to fundamental macroeconomic models and tries to forecast exchange rates based on a rational expectations hypothesis. This set of models uses national incomes, expected inflation differentials, and supply and demand of the exchanged currencies (Papaioannou et al., 2013). Purchasing power parity and interest rate parity (covered and uncovered) are examples of earlier theoretical models that integrate the concept of rational expectation. The second perspective in the theoretical literature has to do with the use of unstructured models and uses time series data for forecasting currency movement. Among these categories of models are regression models (Akbar et al., [2019]; Amano and Van Norden [1998]; Reboredo, [2012]; Chen et al., [2016]; Chen and Chen [2007]; Jiang et al., [2020]; Kisswani et al., [2019]; Lizardo and Mollick [2010]; and Nusair and Olson [2019]). AI technologies enable the mining of hidden, innovative patterns and notable information from massive datasets with no need for prior knowledge of the data. Models such as ANNs, BNNs, DL, and SVRs have been employed for predicting the relationship between financial variables (Chen et al., [2021]; Cogoljević et al., [2018]; Wang et al., [2020]; Li et al., [2019]; Rybinski, [2020]; Wu et al., [2020]; Aggarwal et al., [2021]; Rawat et al., [2021]; and Nasir et al., [2021]).

Other empirical literature uses news items as a textual data source to forecast foreign exchange market movements (Semiromi et al., 2020). For instance, the empirical work of Narayan et al. (2021) utilized news to estimate the US dollar exchange rate against the British pound sterling and discovered that negative news (rather than good news) best forecasts exchange rates. This correlation may be seen during both expansions and recessions; however, it is more pronounced during global recessions and periods of significant depreciation and appreciation. On the fundamental influence of news on exchange rates, Rebitzky (2010) discovers that fundamental news matters more than non-fundamental news. Fundamental news are those that are directly related to announcement that borders on macroeconomic fundamentals that affect exchange rate behavior, by analyzing the impact of interest rate, inflation rate on the relative value of a currency through identifying the primary drivers of a currency's intrinsic value, forex participants are then able to craft informed trading decisions. While non-fundamental news reflects a market's information processing mechanism which may be unrelated to existing macroeconomic fundamentals. For instance, the work of Evans and Lyons (2002) has shown that exchange rates at short horizons are to a significant extent driven by order flow, i.e. excess buyer initiated or seller-initiated trading. News effects on exchange rates do indeed work through two separate channels. While the direct (explicit) news channel incorporates common knowledge information in exchange rates, in the implicit or non-common knowledge, information is processed into prices via order flow.

Some studies also look at exchange rate forecasting in the context of block chain technology to study Bitcoin exchange rates, considering both the technology and economic factors. Among these studies is the work of Li and Wang (2017) who discovered that bitcoin exchange responds to shifts in market conditions and economic fundamentals. Also, Bitcoin exchange is less subject to technological issues and more sensitive to economic fundamentals. Similarly, Palazzi et al. (2020) employs a non-parametric causality test to determine if bitcoin has a nonlinear connection with six currencies and finds that the euro has a direct influence on bitcoin.

A recent study in this area in Nigeria by Olayeni et al. (2020) finds a stable connection between oil prices and exchange rates, although similar studies in Nigeria, such as those by Lawal et al. (2016), Asaleye (2019) and Manasseh (2019), found varying degrees of connection between oil prices and exchange rates using traditional econometrics methodology such as Granger causality, (S)VAR, autoregressive distributed lag (ARDL), which makes the results mixed and inconclusive. For example, the studies by Lizardo and Mollick (2010), Chen and Chen (2007), Benhmad (2012), and Tiwari et al. (2013) found that changes in oil prices cause fluctuation in exchange rates. Other studies such as those by Sadorsky (2000) and Reboredo (2012) show that exchange rate fluctuations can cause variations in oil prices. The reason for these varying results is that these methods are only applicable in dealing with linear problems, and as a pre-condition for their usage, the variable must follow a normal curve.

To fill this literature gap, this study, to the best of our knowledge, is among the first to use machine learning approaches in the form of Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and the Multi-Layer Perceptron (MLP), which are judged to be superior to standard econometrics methods to exhaust and critically study and evaluate the nexus of oil price and exchange rate using data from Nigeria.

3. METHODOLOGY

In order to study the linkage between oil prices and exchange rates using machine learning approaches, we address the following questions.

i. Can oil prices predict exchange rates?
ii. Are bivariate models of exchange rates and oil prices better than univariate models for exchange rates?
iii. If the answer to question 1 is "yes," how do the results behave when the data are decomposed? In other words, which of the results has higher predictive power?

To obtain answers to these questions, we conducted experiments using three deep learning approaches: CNN, LSTM, and the MLP. First, we made our prediction without decomposition. Secondly, our prediction was made with time series data decomposed according to (Huang et al., 1998) Empirical Mode Decomposition (EMD).

This section delves deeper into the technology utilized in this article: the EMD system of data preprocessing, the CNN, the MLP and LSTM. We developed a bivariate forecasting on this basis.

3.1. Empirical Mode Decomposition (EMD)

EMD is a data-driven, unsupervised signal decomposition technique. It offers advantages over all other signal decomposition methods such as the empirical matrix factorization (EMF) in that it is not bound by restrictions that only apply approximately (Zeiler et al., 2010). EMD assumes that a non-linear and non-stationary time series dataset comprises various simple intrinsic oscillation modes. EMD identifies these oscillatory modes in the data and then decomposes them accordingly. The main procedure involved in the EMD technique, also referred to as sifting, decomposes any given dataset ($x(t)$) into Intrinsic Mode Frequencies (IMFs) ($x_n(t)$), and a residue ($r(t)$) so that the signal is denoted as follows:

$$x(t) = \sum_n x_n(t) + r(t) \tag{1}$$

The EMD sifting process as described by Guhathakurta et al. (2008) and as depicted in Figure 1 involves the following steps:

(1) First, local extrema of the time series data are located. All local maxima are then linked by a cubic spline line $U(t)$ that represents the upper envelope of the time series. The same approach is used for the local minima to generate the lower envelope, $L(t)$. The mean of the lower and upper envelope $m(t)$ is derived by:

$$m(t) = \frac{U(t) + L(t)}{2}$$

(2) The mean $m(t)$ is subtracted from the initial time series $D(t)$ resulting in the first component, $h(t)$.

$$h(t) = D(t) - m(t)$$

(3) The $h(t)$ becomes an IMF, if free of riding waves, shown with respect to zero. The symmetry of the upper and lower envelopes, as well as with the numbers of zeros crossing and extremes being the same or differing by only 1.

(4) The $h(t)$ will be treated as the data, and we repeat (1) and (2) again if $h(t)$ is not an IMF.

(5) If the resulting component is the first IMF, the resulting IMF is removed from the initial data and the difference $r(t)$ is a residue. This residue is then treated as if it were the original data, and the sifting process is repeated. A constant or a monotonic function is expected to characterize the final residue.

EMD was used for decomposition of financial time series data in Hong (2011) and Guhathakurta et al. (2008).

3.2. MLP

The MLP is a neural network, which consists of a layer that accepts an input signal to be processed (input layer), a layer that makes predictions about the input (output layer), and an arbitrary number of hidden layers that represent the MLP's computational engine between the input and output layers. Figure 2 shows an MLP with three inputs, two hidden layers, and two outputs.

A node in MLP models an artificial neuron (Yan et al., 2006) that computes the weighted sum of the inputs (x_i), where i corresponds to the input features or variables. This weighted sum is computed in the presence of a bias term, θ*j*, and passed through an activation function,, producing outputs given as:

$$y_j = f_j\left(\sum_i^n w_{ij} x_i + \theta_j\right) \tag{2}$$

where x_i is the n inputs for i = 1,2,…, n. w_{ij} represents the connection weight that exists between the input x_i and the neuron j, f_j (.) represents the activation function of the j^{th} neuron and y_j represents the output. The activation function takes various forms, some of which include: the unit step, linear and logistic (sigmoid) function.

Once the MLP architecture is defined, the network's connection weights are computed via a training process based on the desired output and a training strategy like the back propagation method. Upon completion of training, the MLP will be able to predict changes when new input data are presented to the network (Taud and Mas, 2018). Although MLP has the disadvantage of requiring the temporal dependence of time series data to be specified upfront when designing a model, it is known to perform well on time series forecasting because it efficiently handles noise, easily learns non-linear relationships, supports multivariate inputs, and multistep forecasting (Brownlee, 2018).

3.3. CNN

The CNN is a class of ANNs as well as a DLM for learning spatial hierarchies of features, especially in images datasets. Although mostly used for image classification, it can also be used in solving one-dimensional (1D) problems such as predicting the next value in a time series dataset (Lewinson, 2020). A typical CNN is made up of three (3) layers as depicted in Figure 3: convolution, pooling and fully connected layers.

i. Convolutional layer: this layer applies convolutional filtering to the input data to extract features.
ii. Pooling layer: this layer condenses the series size or images and retains significant features found by the convolution layer.
iii. Fully connected layer: this layer maps the derived features into the final output.

So, the convolution and pooling layers performs the task of feature extraction while the fully connected layer maps the extracted features into outputs. CNN has been used more recently for time series forecasting as demonstrated in (Cui et al., 2016; Koprinska et al., 2018; Wan et al., 2019; Yang et al., 2015; Zhao et al., 2017; Zheng et al., 2014). CNNs support multivariate input and multistep outputs. Hence, they are gaining popularity in time series forecasting as they convert a series of observations into a

Figure 1: Flowchart of EMD of time-series data

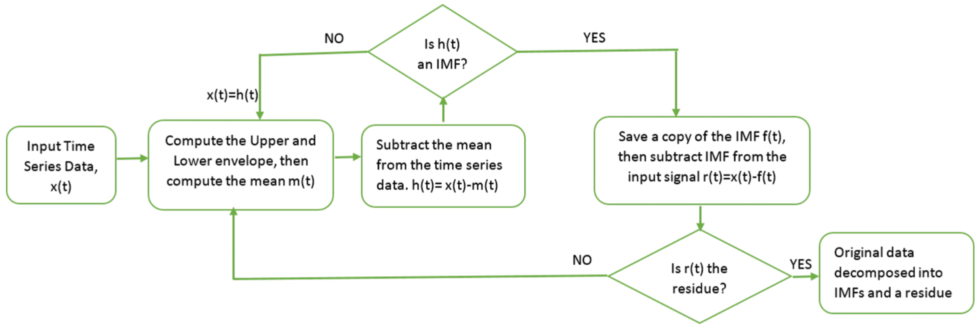


Figure 2: Typical multilayer perceptron

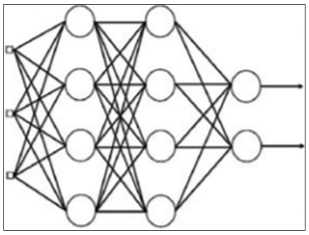
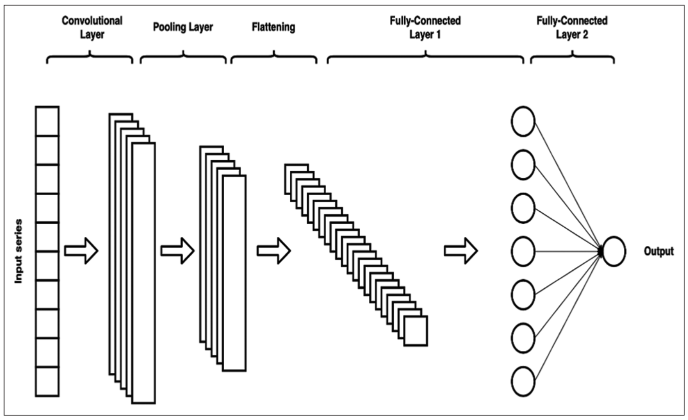


Figure 3: A simplified 1D CNN schema (adopted from (Lewinson, 2020)



one-dimensional image that can be interpreted and distilled into its most important elements (Brownlee, 2018).

3.4. Long Short-Term Memory (LSTM)

LSTM is a form of recurrent neural network (RNN) that learns long-term dependencies. RNNs are ANNs that contain loops (Figure 4) allowing learning from previous information. RNNs are known to work perfectly for small gaps in information dependencies but poorly for long-term information dependencies; hence, the need for LSTM.

The memory blocks are responsible for retaining information. The main steps involved in the LSTM learning strategy are described as follows:

(1) Determination of what information to remove from a cell state: Here the sigmoid (forget gate) layer accepts two inputs: h_{t-1} and x_t, and then outputs a value between "0" and "1" as the value of f_t:

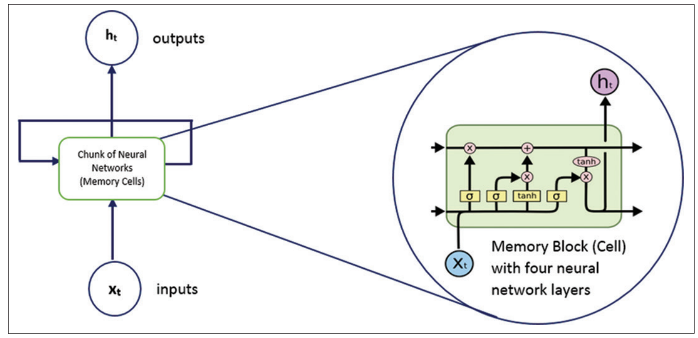
$$f_t = \delta(W_f.[h_{t-1}, x_t] + b_f)$$

Here, h_{t-1} signifies the hidden state from the previous cell and x_t represents the input at that specific time step. If "0" is generated for a specific value in the cell state, then it signifies that the forget gate requires the cell state to fully forget that piece of information. A "1" indicates that the forget gate wishes to recall the complete piece of information.

(2) Determination of what information needs to be updated in the cell state: Three steps are involved here:

a) The sigmoid (input gate) layer determines what information to update. This is described by the equation:

Figure 4: A simplified LSTM architecture



$$i_t = \delta(W_i.[h_{t-1}, x_t] + b_i)$$

b) A vector of new candidate values, $\check{C}_t$ that can be added to the state is created by the tanh layer:

$$\check{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c)$$

c) An update of the old cell state, C_{t-1}, to the new cell state C_t:

$$C_t = f_t \times C_{t-1} + i_t \times \check{C}_t$$

(3) Determination of what to output: Two steps are involved here:

a) Run the sigmoid function that determines the part of the cell state that will be outputted:

$$o_t = \delta(W_0.[h_{t-1}, x_t] + b_0)$$

b) The cell state is passed to the tanh function and then multiplied by the previous output of the sigmoid function:

$$h_t = o_t \times \tanh(C_t)$$

LSTM offers the ability to explicitly address order across observations while learning mapping functions between inputs and outputs, in addition to the benefits afforded by both MLP and CNN. In summary, the use of CNN, MLP and LSTM models for forecasting time series data is becoming the most promising application of deep learning approaches (Brownlee, 2018).

3.5. Data Sources

In this study, two variables for monthly data are used: the actual exchange rate of Nigeria and the international benchmark price for crude oil. Monthly data (January 1989-December 2020) on Nigeria's exchange rates, totaling 384 samples in 31 years, were collected from the Central Bank of Nigeria Statistics Bulletin. Corresponding monthly data for benchmark crude oil price were also composed from the statistical database of the United Nations Conference on Trade and Development (UNCTAD). A trend presentation of the exchange rate and oil price is as illustrated in Figure 5.

In constructing the DLMs, the data were separated into two datasets: the training dataset and the testing dataset. Of the 384 data items, 264 monthly data points for 20 years (from January 1989 to December 2009) were used as training datasets. The testing dataset comprised 120 monthly data items from 2010 to 2020 (11 years). Statistical descriptions of the training and testing datasets are shown in Table 1 while Table 2 describes the data model used.

3.6. Validation method

In this section, verification of the significance and performance of the developed forecasting models were conducted using the DM test and the Akaike information index (AIC).

3.6.1. The DM test

The DM test (Diebold and Mariano, 2002) is a hypothesis testing strategy to quantitatively evaluate forecasting accuracy. This study used the DM test to determine whether there is a substantial difference between the univariate and bivariate models developed. The DM test was also used to evaluate the effectiveness of the bivariate models. What follows is a description of the steps used to conduct the DM test (Chen et al., 2014):

Let,

y_t = actual time series data
$\hat{y}_{i,t}^h$ = i^{th} competing h-step forecasting series
$e_{i,t}^h$ = forecasting errors for the i^{th} competing models,

where,

i = 1, 2, 3,…, m (m is the number of forecasting models).

Determine the loss function's accuracy for each forecast:

$$L\left(y_t^h, \hat{y}_{i,t}^h\right) = L(e_{i,t}^h)$$

where,

$$e_{i,t}^h = y_t^h - \hat{y}_{i,t}^h$$

Determine if one forecasting model predicts more accurately than another by testing the accuracy equality hypothesis.

$H_0 : L\left(e_{1,t}^h\right) = L(e_{2,t}^h)$, when comparing two forecasting models and $H_1 : L\left(e_{1,t}^h\right) \neq L(e_{2,t}^h)$.

So, the DM test is built on the loss differential: $L(e_{(1,t)}^h) - L(e_{(2,t)}^h)$ and the DM statistics are defined as:

$$DM = \frac{\frac{1}{T}\sum_{n=1}^{T} L\left(e_{i,t}^h\right) - L(e_{i,t}^h)}{\sqrt{\frac{S^2}{T}}} \tag{3}$$

Here, S^2 shows the variance estimation of $L\left(e_{1,t}^h\right) - L(e_{2,t}^h)$.

The null hypothesis states that the predictive results of multiple predictive models do not vary substantially. Conversely, the alternate hypothesis states that two forecasting models have substantially different predictive results. The DM statistic is a random variable with a normal distribution and a degree of significance defined as $\propto Z_{\alpha 2}$ is the critical value at certain level. The null hypothesis (H_0) is rejected when the critical value is less than the absolute value of the DM.

3.6.2. The Akaike information index (AIC)

The AIC (Akaike, 1998) is a technique that focuses on in-sample fit to evaluate a model's probability of forecasting future values. We also used the AIC to test the predictive efficiency of the univariate and bivariate models developed. The AIC index formula is defined as follows:

$$AIC = n \times log\left[\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)\right] + 2k \tag{4}$$

The best model is identified as one that has the least AIC value among other models (Mohammed et al., 2015).

4. EXPERIMENT AND FINDINGS

We conducted several experiments to evaluate the effect of data preprocessing as well as oil prices on exchange rate estimation, and obtained convincing results.

Figure 5: Oil price and exchange rate trends 1989-2020. In the chart, 2014M01 signifies the 1st month (January) of 2014

Table 1: Statistical description of dataset

Dataset	Sample	Number	Statistical Indicator			
			Max	Min.	Mean	Std.
Oil Price	All Samples	384	138.74	10.22	48.88	33.15
	Training Sample	264	138.74	10.22	36.44	26.34
	Testing Sample	120	128.00	14.28	77.27	29.57
Exchange Rate	All Samples	384	381.00	7.04	125.65	97.17
	Training Sample	264	152.30	7.14	76.41	55.02
	Testing Sample	120	381.00	150.48	233.24	77.41

Our study uses the following DLM evaluation criteria: mean absolute error (MAE), mean absolute percentage error (MAPE), mean of error squares (MSE), and sum of error squares (SSE) to validate the prediction model's precision. We also used indicators such as correlation coefficient (R^2) and root mean squared error (RMSE). Table 3 shows the mathematical representation of these evaluation criteria in formulas. $\hat{Y}_i$ represents the true sequence, Y_i represents the forecasting sequence, $\bar{Y}_i$ represents the mean of the forecasting sequence, and N represents the number of the samples.

4.1. Results and Analysis

This section presents the findings of our experiments. The relationship between oil price and actual exchange rate was successfully examined. The impact of oil price data on real exchange rate estimation was also established.

Table 2: Input/output model

	Exchange rate univariate model						
	Input (Exchange rate)						Output
Training	Y_1		Y_2		Y_3		Y_4
	Y_2		Y_3		Y_4		Y_5
	Y_{249}		Y_{250}		Y_{251}		Y_{252}
Testing	Y_{250}		Y_{251}		Y_{252}		Y_{253}
	Y_{357}		Y_{358}		Y_{359}		Y_{360}
	Oil-Exchange rate bivariate model						
	Input (Oil price and Exchange rate)						Output
Training	X_1	X_2	X_3	Y_1	Y_2	Y_3	Y_4
	X_2	X_3	X_4	Y_2	Y_3	Y_4	Y_5
	X_{249}	X_{250}	X_{251}	Y_{249}	Y_{250}	Y_{251}	Y_{252}
Testing	X_{250}	X_{251}	X_{252}	Y_{250}	Y_{251}	Y_{252}	Y_{253}
	X_{357}	X_{358}	X_{359}	Y_{357}	Y_{358}	Y_{359}	Y_{360}

Y represents the exchange rate while X represents the oil price.

Table 3: Model evaluation metrics

Metric	Description	Equation
MSE	Mean of error squares	$MSE = \frac{1}{N} \times \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2$
RMSE	Square root of the mean of square errors	$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2}$
MAE	Mean absolute error of N forecasted outcomes	$MAE = \frac{1}{N} \times \sum_{i=1}^{N} \left\lvert Y_i - \hat{Y}_i \right\rvert$
R_2	Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{N} \left(Y_i - \bar{Y}_i\right)^2}$
MAPE	Mean of N absolute percentage error	$MAPE = \frac{1}{N} \times \sum_{i=1}^{N} \left\lvert \frac{Y_i - \hat{Y}_i}{Y_i} \right\rvert \times 100$
SSE	Sum of error squares	$SSE = \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2$

4.1.1. Experiment 1: Correlation analysis between oil prices and exchange rates

Kendall Tau and Spearman rank correlation tests were utilized to examine the correlation between oil prices and exchange rates. The correlation results showed that oil prices and exchange rates are statistically significant, indicating a positive co-movement between variables as indicated in Table 4 below.

4.1.2. Experiment 2: Data preprocessing effects

This experiment was designed to investigate whether the data preprocessing technique has any impact on predictive results. Pairwise comparisons of three models (MLP vs. EMD-MLP, CNN vs. EMD-CNN, and LSTM vs. EMD-LSTM) are used to discuss the findings. Figures 6 and 7 illustrate the graphical comparison of these models while Table 4 shows the basic experimental findings followed by a brief description:

a) The EMD-MLP model achieves the best accuracy in the first contrast (MLP vs. EMD-MLP) for one-step forecasting: the six error predictor values are 2.61, 6.83, 2.6, 0.98, 1.14, and 273.52. The MLP model has the following six error indicator values: 3.62, 13.14, 2.76, 0.99, 1.01, and 525.87, hence, its prediction performance is significantly lower than the EMD-MLP model.

b) The second comparison (CNN vs. EMD-CNN), we obtained MAE values for the unprocessed CNN model as: 2.63, 5.56, and 6.32, respectively, in all prediction stages. The EMD-CNN model, on the other hand, has better MAE values of 0.83, 1.16, and 1.52, respectively. The values of the MAPE, MSE, and SSE error metrics are as illustrated in Table 4a and 4b.

c) The data preprocessed models also outperform the unprocessed (data) models in the third contrast (LSTM vs. EMD-LSTM), with MAPE values of 0.41, 0.6, and 0.81 as against 1.75, 2.11, and 2.41 respectively. The same can be said for other error metrics as described in Table 4.

4.1.3. Experiment 3: Comparison between bivariate and univariate model

This experiment contrasts the bivariate and univariate model. There are three bivariate models: the Oil Price vs. Exchange Rate MLP, CNN, and LSTM models. Table 5 demonstrates the specifics of the experimental findings.

a) Bivariate EMD-MLP model: The bivariate EMD-MLP model has better statistical results than univariate model-based models. In the single step forecasts, the bivariate EMD-MLP outperforms other models with MAPE values of 0.66 and MAE values of 1.45. Based on the findings, it is also apparent that the bivariate model outperforms univariate models.

b) Bivariate EMD-CNN model: In one-step estimation, the EMD-CNN bivariate model achieves optimum precision, with excellent error indicator values of 0.59, 0.35, 0.51, 0.99, 0.34, 14.26 as against 0.92, 0.86, 0.83, 0.99, 0.48, 34.51 for the Univariate EMD-CNN model. Furthermore, based on the

Table 4: Correlation of crude oil price and exchange rate

	Kendall's tau_b	Spearman's rho
Oil Price	0.68*	0.62*
Exchange rate	0.52*	0.47**

**, * stands for 5% and 10% level of significance

Figure 6: Comparison of Univariate (Undecomposed) deep models

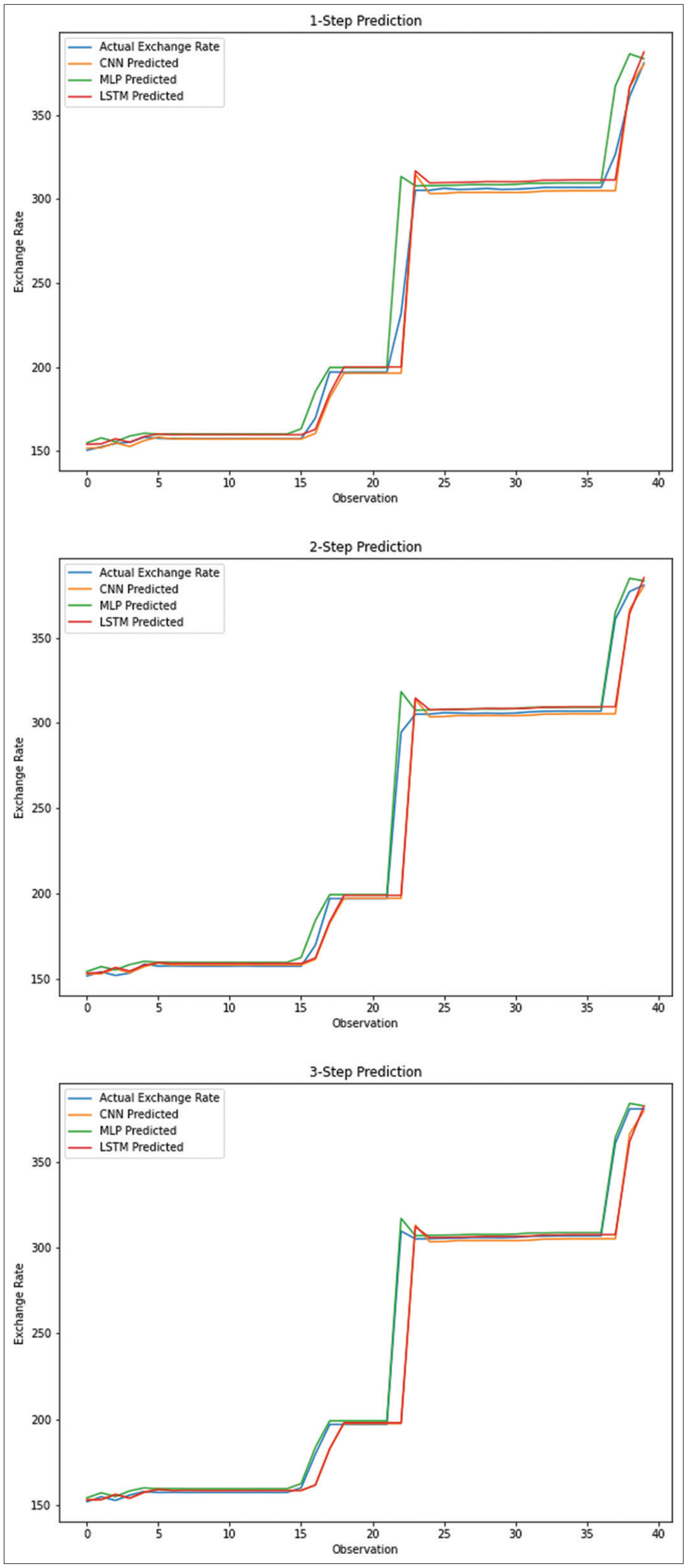
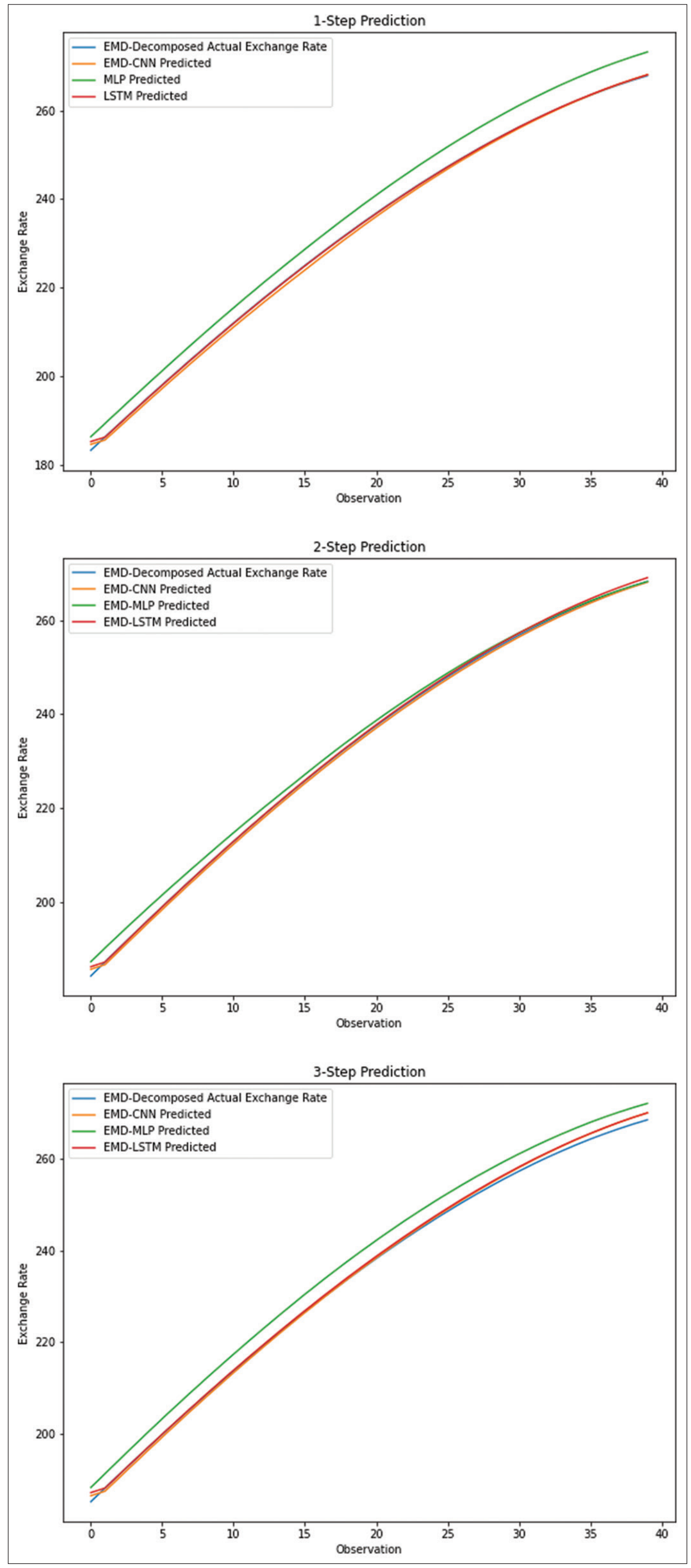


Figure 7: Comparison of Multivariate (Decomposed) deep models



six error metrics obtained in the EMD-CNN multistep (2 steps and 3 steps) prediction, it can be inferred that the bivariate model has greater predictive accuracy related to the univariate model in forecasting exchange rates.

c) Bivariate EMD-LSTM model: In a one-step estimation, the EMD-LSTM bivariate model achieves better precision, with the best error indicators values of 1.05, 1.11, 0.71, 0.99, 0.28, 44.5 as against 1.22, 1.5, 1.02, 0.99, 0.41, and 60.33 for the univariate EMD-LSTM model.

Remarks: From the findings of the one-step and multi-step prediction in Experiment 3, the error index value generated by the bivariate forecasting model is clearly less compared to that produced by the univariate models. As a result, the bivariate forecasting model

Table 4a: Results from Experiment II

Dataset	Model	RMSE			MSE			MAE		
		1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Univariate	MLP	3.62	4.19	12.7	13.14	17.59	162.8	2.76	3.12	6.15
	CNN	6.91	17.76	20.08	47.76	315.43	403.28	2.63	5.56	6.32
	LSTM	6.95	17.93	20.54	48.39	321.72	421.96	4.01	5.75	6.73
	EMD-MLP	2.61	2.81	3.06	6.83	7.89	9.38	2.6	2.81	3.06
	EMD-CNN	0.92	1.29	1.7	0.86	1.67	2.9	0.83	1.16	1.52
	EMD-LSTM	1.22	1.77	2.37	1.5	3.14	5.64	1.02	1.49	2.01

Table 4b: Results from Experiment II

Dataset	Model	R2			MAPE			SSE		
		1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Univariate	MLP	0.99	0.99	0.97	1.01	1.19	2.42	525.87	703.96	6513.39
	CNN	0.99	0.94	0.93	1.18	2.09	2.36	1910.75	12617.54	16131.25
	LSTM	0.99	0.94	0.93	1.75	2.11	2.41	1935.97	12868.95	16878.41
	EMD-MLP	0.98	0.98	0.98	1.14	1.22	1.32	273.52	315.9	375.57
	EMD-CNN	0.99	0.99	0.99	0.35	0.48	0.63	34.51	66.82	116.16
	EMD-LSTM	0.99	0.99	0.99	0.41	0.6	0.81	60.33	125.81	225.69

Table 5a: Experiment III findings comparison

Dataset	Model	RMSE			MSE			MAE		
		1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Univariate	MLP	3.62	4.19	12.7	13.14	17.59	162.8	2.76	3.12	6.15
	CNN	6.91	17.76	20.08	47.76	315.43	403.28	2.63	5.56	6.32
	LSTM	6.95	17.93	20.54	48.39	321.72	421.96	4.01	5.75	6.73
	EMD-MLP	2.61	2.81	3.06	6.83	7.89	9.38	2.6	2.81	3.06
	EMD-CNN	0.92	1.29	1.7	0.86	1.67	2.9	0.83	1.16	1.52
	EMD-LSTM	1.22	1.77	2.37	1.5	3.14	5.64	1.02	1.49	2.01
Bivariate	EMD-MLP	1.64	4.67	5.32	2.69	21.86	28.35	1.45	4.63	5.19
	EMD-CNN	0.59	1.05	1.07	0.35	1.12	1.15	0.51	0.85	0.9
	EMD-LSTM	1.05	1.29	1.54	1.11	1.67	2.38	0.71	1.13	1.37

Table 5b: Experiment III findings comparison

Dataset	Model	R2			MAPE			SSE		
		1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Univariate	MLP	0.99	0.99	0.97	1.01	1.19	2.42	525.87	703.96	6513.39
	CNN	0.99	0.94	0.93	1.18	2.09	2.36	1910.75	12617.54	16131.25
	LSTM	0.99	0.94	0.93	1.75	2.11	2.41	1935.97	12868.95	16878.41
	EMD-MLP	0.98	0.98	0.98	1.14	1.22	1.32	273.52	315.9	375.57
	EMD-CNN	0.99	0.99	0.99	0.35	0.48	0.63	34.51	66.82	116.16
	EMD-LSTM	0.99	0.99	0.99	0.41	0.6	0.81	60.33	125.81	225.69
Bivariate	EMD-MLP	0.99	0.96	0.95	0.66	1.98	2.2	107.82	874.49	1134.3
	EMD-CNN	0.99	0.99	0.99	0.21	0.34	0.37	14.26	44.93	46.2
	EMD-LSTM	0.99	0.99	0.99	0.28	0.46	0.56	44.5	67.15	95.22

performs better than the univariate forecasting model with respect to accuracy. The findings suggest that oil price information has a significant influence on actual exchange rate forecasts.

5. DISCUSSION

This section further discusses the experimental findings and investigates the effect of benchmark oil prices on Nigeria's actual exchange rate. To further validate our experimental results, we first assess the prediction effectiveness of our univariate models and bivariate models using AIC. Then, to determine the bivariate model's predictive validity, we used the DM test.

5.1. Results of the Akaike Information Index

It can be deduced from the experimental findings in Table 6 that almost all bivariate models have a lower AIC value than the univariate one. The Bivariate models demonstrating smaller AIC values are boldly highlighted in Table 6. The outcome is in line with previous experimental findings, demonstrating the two-variable model's superiority.

Table 6: AIC results comparison

Model	1-step	2-step	3-step	Model	1-step	2-step	3-step	Model	1-step	2-step	3-step
Univariate											
MLP	133.2	155.79	234.62	CNN	160.38	236.15	245.92	LSTM	169.33	236.53	249.54
EMD-MLP	86.59	89.17	91.6	EMD-CNN	13.29	36.15	51.25	EMD-LSTM	32.19	54.05	75.44
Bivariate											
EMD-MLP	44.22	130.54	140.58	EMD-CNN	−19.77	14.92	14.11	EMD-LSTM	9.81	24.8	41.43

Table 7: DM test results

Model	EMD-MLP (Bivariate)		
	1-step	2-step	3-step
MLP (Univariate)	5.8068	8.1477	7.9498
EMD-MLP (Univariate)	2.2439	2.4016	2.4015
Model	**EMD-CNN (Bivariate)**		
	1-step	**2-step**	**3-step**
CNN (Univariate)	7.8938	6.2543	5.8903
EMD-CNN (Univariate)	1.7786	2.2708	1.7437
Model	**EMD-LSTM (Bivariate)**		
	1-step	**2-step**	**3-step**
LSTM (Univariate)	7.8047	6.2284	5.7156
EMD-LSTM (Univariate)	2.7099	2.8937	2.5521

5.2. Results of the DM test

The DM test that was used to determine the bivariate model's predictive validity, and the model's accuracy dependent on statistical thought was then checked. The bivariate model is compared to the corresponding univariate model, with detailed results in Table 7.

When comparing univariate models to bivariate models, all DM values are higher than the critical value of 10%, hence the null hypothesis of "no significant difference between the prediction of different predictive models" is rejected. This signifies that the predictive ability of the bivariate models differs considerably from that of univariate models.

6. CONCLUSIONS AND IMPLICATIONS

While deep learning has tremendous applications for financial and foreign exchange rate predictions, what are the practical implications? Financial specialists and policy makers must be ready to comprehend and cognitively accept the opportunities and challenges introduced by the recent waves of technology as effective and efficient decision-making instruments. As a consequence of the experimental results, there is a benefit to estimating exchange rates using oil prices. In addition, when preprocessed datasets are used, the DLMs developed perform more efficiently. The application of deep learning in the accurate forecast of exchange rates has a substantial impact on the global market and local economic policy formation. Because the purchasing power of various currencies is determined by the fluctuations of the exchange rate, significant investment and trading strategies require precise exchange rate forecasting. It is evident that strategies that embrace AI have the potential for resulting in exponential economic development and financial rewards.

Forecasting exchange rates has become a common topic in recent times. Accurate exchange rate forecasting is a research area that can help governments and businesses alike to make significant and intelligent decisions. Nevertheless, due to the intricacies of financial fluctuations and the interplay of several economic indicators, exchange rate forecasting remains a challenging and complex subject. This paper began by examining the correlation between oil prices and exchange rates, then went on to further scrutinize the effectiveness of using oil price in exchange rate forecasting. The Kendall Tau and Spearman rank correlation result indicated that oil price and exchange rate are statistically significant, indicating positive co-movement between them. By way of comparison, we built a univariate and bivariate model using CNN, LSTM, and MLP to access the predictive performance of the models. Subsequently, we utilized a data preprocessing mechanism (EMD) to evaluate the predictive performance of the models developed, with and without decomposition.

Our results underscore the importance of global oil prices in the exchange rate movement of an oil producing state like Nigeria. Our findings corroborate those of Beckmann et al. (2016); Lizardo and Mollick (2010); Inumula and Solanki (2017) and Fratzscher et al. (2013) that currencies of oil-exporting nations gain in relation to the US dollar. However, the models applied in these studies have some causality issues or assume certain levels of linearity and normal distribution. The AI approaches used overcome these limitations and appropriately predict the direction of causation. The bivariate prediction model offers greater predictive ability as compared to univariate prediction models. Of the three bivariate models, the EMD-CNN model offers the best predictive performance, with values for the six-error metrics as 0.59, 0.35, 0.51, 0.99, 0.34, and 14.26 representing RMSE, MSE, MAE, R^2, MAPE, and SSE respectively. The studies also indicate that global benchmark oil price has a significant direct influence on exchange rate forecasting, and that oil price data may be especially useful in developing accurate exchange rate forecasts.

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