Modeling and Forecasting Commodity Futures Prices: Decomposition Approach

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ABSTRACT Price instability is a paramount concern since commodity prices are associated with the livelihood and the economy of a nation as a whole; any extraordinary price fluctuation in the futures market shows that forecasts in commodities is an essential venture. The difficulties in predicting commodity prices are due to the unpredictability of the world's financial issues, fiscal dispensation, the speculative market's exacerbation, and several other elements. This study aims to model and forecast the market price of commodity futures. We applied decomposition techniques, empirical mode decomposition (EMD), and variational mode decomposition (VMD) to three commodities: corn, crude oil, and gold over the commodity spot market prices. We used the Granger causality test to establish mutual relationships amongst the three commodity futures prices. Three commodity price data with different periods were decomposed into several intrinsic modes. Using three forecasting performance evaluation criteria, statistical measures such as mean absolute error (MAE), root mean square error (RMSE), and mean percentage error (MAPE) to compare the capabilities of the suggested models. We also introduced Diebold Mariano (DM) test in selecting the optimal models for each commodity, since MAE, RMSE and MAPE have some shortcomings. We found that the combined models outperformed the individual back propagation neural network (BPNN) and autoregressive integrated moving average (ARIMA) models in forecasting corn and crude oil futures prices series, while BPNN emerged as the optimal model for predicting gold futures prices series. Variational mode decomposition emerged as the ideal data pre-treatment method and contributed to enhancing the predicting ability of the BPNN and the ARIMA models. The empirical results showed that models combined with decomposition methods predict commodity futures prices accurately and can easily capture the volatility in commodity futures prices.

INDEX TERMS Back propagation neural network, commodity price, empirical mode decomposition, forecasting, Granger causality test, variational mode decomposition.

NOMENCLATURE

ADMM	Alternate direction method of multipliers
MI	Machine intelligence
ARMA	Autoregressive moving average
BPNN	Back-propagation neural network
COMEX	Commodity Exchange Inc
EEMD	Ensemble empirical mode decomposition
EMD	Empirical mode decomposition
EWT	Empirical wavelet transform
GA	Genetic algorithm
GDP	Gross domestic product
IMF	Intrinsic mode functions
LSSVR	Least squares support vector regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MRS	Markov regime-switching
MS-GARCH	Markov switching generalized autoregressive conditional heteroskedasticity

MSR	Markov switching regressive
NN	Neural network
RBFNN	Radial basis function neural network
SSA	Singular spectrum analysis
SST	Synchrosqueezed transform
SVR	Support vector regression
VMD	Variational mode decomposition
VAR	Vector autoregressive
JB	Jarque-Bera
Skew	Skewdeness
Min	Minimum
Max	Maximum
Sd	Standard deviation
Kurt	Kurtosis
DM	Diebold Mariano
DM-AE	Diebold Mariano test based on absolute error loss
DM-SE	Diebold Mariano test based on square error loss
DM-PE	Diebold Mariano test based on percentage error loss
SE	Square-error
AE	Absolute-error
PE	Percentage error

I. INTRODUCTION

Current developments in the commodity market have remarkable effects on global economy. Commodity market such as crude oil, corn, and gold play a consequential role in the global financial markets. Indeed, the price of these commodities is highly volatile and directly affects the global market activities [1], [2]. The futures prices of these three commodities are influenced by factors such as demand and supply, market speculations, economic growth, national schemes and unforeseen circumstances like spillover effect, an outbreak of a pandemic, war, and recent global debt crisis [3]. These sophisticated factors are the leading components of the sharp price variations of these commodities spot market prices. The price instability of the above commodities market is a major concern as venture capitalists expect to make a profit from their investments, hence, price investigation of crude oil, corn and gold can provide investors the necessary macroeconomic details to strategize and minimize the cost of doing business and increase profit. The price series of the aforementioned commodities are non-linear and non-stationary, which make it strenuous to develop models to evaluate the price pattern of these commodities. Pragmatic investment decision-making, which can help venture capitalists and policymakers to curb the risk caused by price fluctuation, therefore, can only be attained through explicitly predicting the futures market.

The United States of America, China and the European Union are considered as the world's leading economies, and major consumers of corn, crude oil and gold. Statistics shows that the United States is the number one producer and purchaser of corn globally. In 2019/2020 farm season alone,

the United States utilized over 12.30 billion tonnes of corn, preceded by China. China used more than 10.98 billion tonnes of corn during the same period. The European Community is the number three consumer of corn worldwide [4]. This indicates that corn as a commodity is pivotal in the day-to-day organization of the economy of the above-mentioned countries. The International Energy Agency (IEA) 2019 record shows that, America and China are the principal purchasers of crude oil in the world; these countries utilized roughly 19.4 million barrels and 14 million barrels daily, separately. Gold is an internationally accepted commodity used to estimate wealth and benchmark for inflation. It has a tendency of maintaining its value over a long period. The price of gold depends on the production cost and what amount people are prepared to offer. According to the futures price discovery mechanism report, corn, crude oil, and gold prices are influenced by macroeconomic schemes [5], hence, these commodities are very essential in giving futures spot market price information. Consequently, predicting the price series of aforesaid commodities, therefore, is anticipated not only to reduce the unsteady and decline the risk in commodity markets, but can also assist governing bodies to make prudent and sustainable economic decisions.

Crude oil, corn, and gold markets are deemed as the topmost unstable, correlative and conglomerate in the commodity market and responsive to macroeconomic schemes [4]. The above-mentioned commodities were selected over the commodity spot market price to perform this experiment, which focussed on forecasting the price dynamics in energy, agriculture and industrial metal. In the global economy, corn, crude oil and gold markets are very crucial, therefore, the price study of these commodities is important for any sustainable future planning, due to the correlative relationship among price, supply and demand. For instance, a small increase in oil price often leads to increasing inflation, thereby, affecting importing countries' economies, although, reduced oil prices also bring about the economic downturn and political uncertainty in nations that export oil for economic development. The volatility of oil prices causes economic instability as research has shown that a relatively small rise in crude oil prices has a significant effect on worldwide economy [6]. An increase of 10% of the price is equivalent to 0.6% to 2.5% of Gross Domestic Product (GDP) growth for the USA [6], [7]. High oil prices increase the cost of doing business, and these costs are ultimately passed on to consumers and businesses.

Motivated by the above-mentioned reasons, we suggested an advanced signal identifier, EMD and VMD approach, to break down crude oil, corn, and gold prices data to forecast commodity spot markets' prices. This study employs EMD and VMD methods to study and forecast the futures prices of corn, crude oil, and gold. By analyzing and forecasting the price series of these chosen commodities markets, this investigation would add to the existing study as follows:

- It will provide a detailed analysis of the causal relationship among three types of commodities

- The data pre-treatment effect of EMD and VMD techniques will be horizontally compared using forecasting performance measures.
- The forecasting capability of BPNN and ARIMA can be improved.
- the economic interpretations of these commodities' price movements can be established, and
- It may be established that the combined models have high precision in commodity price forecasting.

The rest of the article is arranged as follows. In the second part, we discuss the related studies, talk about the data and describe the methodology of the Granger causality test, EMD, and VMD processes, as well as the BPNN and ARIMA forecast approach. In the third part, we discuss the empirical results and assess the suitability of the suggested models and the forecast ability relative to BPNN as a standard model and ARIMA as a relative model to evaluate the resilience of the suggested hybrid models. In the fourth part, we discuss obtained findings and conclude our study, where possible economic interpretations of the findings and subsequent developments are also presented in the fifth part.

A. RELATED WORKS

Generally, commodity markets such as the energy market, agricultural product market, and industrial metal market are interrelated due to free access of the information in the open market, which implies that individual markets information can influence other markets. Many studies have been conducted on the commodity futures markets price fluctuations. However, the unpredictability of global events, such as the 2008 European debt crisis, recently outbreak of COVID-19 and trade wars, can consequentially affect the commodity markets. For instance, crude oil, corn and gold markets are highly influenced by economic policies, events of global markets, demand and supply. These factors can either have long-term or short-term effects on the future market [8]. Due to the volatility and uncertain nature of these commodities markets, their price series is non-linear and non-stationary, hence, developing models to minimize the danger posed by unforeseen circumstances and frequent price variations is time consuming and has attracted many researchers attention recently [9].

Initially, researchers suggested single traditional statistical models to forecast commodity futures market prices fluctuations. Reference [10]–[12] used the vector autoregressive (VAR) model, autoregressive integrated moving average (ARIMA), and Markov regime-switching (MRS) models in forecasting the economic time series. Owing to the drawbacks of conventional approaches, predicting models that depend on the machine intelligence approach (MI) [12], [10] were introduced to deal with the nonlinear pattern in the financial time series, like the neural network [14], 12], support vector machine (SVM) [15], [12], and genetic algorithm (GA) [16].

A large number of researchers have utilized the neural network (NN) in forecasting commodity market prices. Reference [17] suggested an enhanced neural network (NN)

to secure an accurate simulation of gold futures prices. Some studies have shown that combined methods optimize predicting capabilities of models [18]–[21]. A lot of decomposition and constructional techniques were proposed before the development of forecasting technologies: Wavelet method [22]–[25], singular spectrum analysis (SSA) [26], [27]. Reference [20] used a singular spectrum analysis technique combined with a radial basis function neural network (RBFNN) to forecast corn, crude oil, and gold prices series with different periods. They reported that the integrated model outperforms the single model approach.

Furthermore, [23] employed a wavelet framework and combined it with a multivariate ARMA-GARCH to examine the oil price, foreign exchange rates, inflation rates, and stock market prices at different periods, nevertheless, SAA and wavelet methods have some inevitable setbacks. The performance of SSA and wavelet transform is based on explicitly and a priori identification of the signal forming part of the series. This selection process may affect the frequency investigation. This normally gives rise to the selection of false series. Wavelet is non-adaptive in nature. VMD and EMD do not need a priori test since the decomposition depends on the local data characteristics, hence, they have not been extensively used in the analysis of commodity futures prices. This study, therefore, proposes these two decompositions, EMD and VMD techniques, based on their decomposition frameworks, to forecast commodity futures prices.

EMD is an adaptive method proposed as a tool in addressing non-linear and non-stationary time series [28]. EMD is a data-driven, empirical, and robust data pre-treatment method suggested, particularly for non-linear and non-stationary data series. The main work of EMD is to break down the actual series into a specific number of intrinsic mode functions (IMFs) and residue based on local characteristics with regard to scale and frequency. For example, an IMF related to commodity time series which lasts for a period of three months is referred to as a seasonal event.

Analysts have used EMD in studying economic and financial reports. For example, in modelling agricultural products ([29], [30]), electricity price [31]–[33]), exchange rates [34], [35], [7]; gold prices [36], [37]), crude oil prices [38], [39], [13], [40], [41] carbon prices [42] and engineering processes [35]. In addressing non-linear and non-stationary characteristics in economic data series, like exchange rates, [35] utilized differential empirical mode decomposition (DEMD) and combined with the support of vector regression (SVR) to forecast exchange rates. The report revealed the hybrid model, DEMD-SVR was superior to the state-of-art Markov switching generalized autoregressive conditional heteroskedasticity (MS-GARCH) and Markov switching regressive (MSR) models.

In assessing the economic impacts of sanctions on Ukraine's ruble exchange rate, [43] suggested the EMD technique and integrated it into the Hurst exponent. Based on the effective market theory, they reported that sanctions from other countries have no influence on the ruble exchange

rate and deduced that exchange rate markets have a long memory.

To evaluate the consequences of China's foreign export trade policy on tin price, [44] proposed the EMD and combined it with counterfactual analysis. They employed four decomposition methods in their assessments and chose the EMD technique as the optimal method. It was further reported that China's foreign export trade policy on tin price has no significant impact on tin price, rather the termination of export trade policy gave rise to the oversupply of tin on the global market, which led to decrease in the prices of tin eventually; this caused short-term variation in the global tin market, showing that trade policy, and price are responsible for tin market price fluctuations.

The spillover effect is another global issue that affects the commodity market either positively or negatively, but is more often related to negative effects. In studying the spillover effect between electricity and carbon markets, [45] proposed the EMD method to decompose both commodities price series into individual IMFs; the spillover effects of the two markets were detected by using a conditional value at risk. The evaluation results revealed a positive spillover effect of carbon commodity market over electricity commodity market prices, however, there were negative spillover effects of the electricity commodity market over the carbon commodity market prices.

"Reference [46]" utilized the EMD-BPNN model to forecast a near-term passenger movement in metro bus organization using passengers' historical movement data. A short-lived passenger movement series data was decomposed into several IMF units using EMD. The result revealed that the combined EMD-BPNN method outperforms the single BPNN model, without decomposition, in forecasting the short-term passenger movement.

"Reference [47]" also used EMD and wavelet decomposition to study the classification and predicting of arrival data of venture clusters and reported that the EMD could extract the hidden patterns within the data stream. Again, the results showed that EMD outperforms the wavelet-based models in terms of extracting various patterns in the data.

To enhance EMD and EEMD by decreasing extreme points issue and mode-mixing, [48] developed VMD. It is a non-recursive and bandwidth-limited maximization decomposition technique which makes use of Wiener filtering and Hilbert transform. VMD is capable of decomposing time series data to any desirable modes. It assumed that each and every mode has a center frequency which is limited bandwidth. The center frequency can minimize the summation of evaluated bandwidth of every single mode such that each mode is equal to the original data. In addition, it is good for decomposing non-linear and non-stationary data.

Researchers have recently utilized VMD in many study areas. For example, in determining the determinants of commodity futures prices fluctuations, [49] used VMD to break down corn, crude oil and gold price data into their respective modes. Reference [50] used VMD to study daytime stock market prices at different frequencies. Reference [51] evaluated the performance of VMD over empirical wavelet transform (EWT) utilizing six different powers to study power distinction. The results showed that VMD outperformed the EWT in respect of the quality data separation and recognition reliability. Reference [52] utilized VMD to predict rainfall-runoff. The results revealed that VMD based methods performed better in terms of efficiency.

In forecasting the stock price index, [53] proposed VMD-LSTM to predict stock market price. VMD was used to pre-process the original stock market price data into several modes. The outcome was analyzed by comparing VMD-LSTM and EMD-based models. It was conclusively reported that the VMD-LSTM model augments the predicting of a stock market price index. The integrated models outperformed the single models, and predicting precision of VMD-based model was superior to the EMD-based model.

In the quest to understand the volatility in price movement of the natural rubber market in Shanghai, [8] developed VMD- based models to study rubbers' futures series. A combined model, VMD-BiGRU was formed to predict short-term rubbers' futures prices of Shanghai Future Exchange. The VMD technique was reported as the optimal method in evaluating natural rubber's market, and which could bring out inherent components related to rubber market price variations. Likewise. Reference [54] made use of VMD in predicting the crude oil market price data. The VMD-based model was suggested and integrated with LSTM and moving window (MW) to construct a combined model, called VMD-LSTM-MW to predict daily and monthly crude oil price. The report indicated that the VMD-LSTM-MW model has high-level forecasting ability than a single-energy-based (SE) model.

Furthermore, in the time-frequency analysis of gold future market price, [55] engaged the VMD technique to disintegrate the actual data of gold to study the spontaneous price movement of gold future market price. The VMD-based model was built on independent component analysis (ICA) and gate recurrent unit neural network (GRUNN) method, defined as VMD-ICA-GRUNN. It was concluded that the hybrid model, VMD-ICA-GRUNN, has high forecasting accuracy than single models, such as ARIMA,RBFNN, LSTM, GRUNN and ICA-LSTM.

"Reference [56]" applied hybridization technique to predict crude oil markets, particularly, the West Taxes Intermediate (WTI) market, the Brent market, and the OPEC market. They combined VMD and quantile regression neural Network (QRNN) to compose a joint model known as VMD-QRNN to study price instability in these three markets and reported that the suggested method accurately predicts the volatility of the aforementioned markets, and improves the forecasting precision of QRNN.

"Reference [57]" adopted VMD to study the behavior of hydroacoustic signal using radar. The VMD was applied to separate the hydroacoustic data into different modes to

evaluate the velocity of each and every signal. A VMD-SVM model was formulated to distinguish underwater acoustic signals and compare them to three simulation signal techniques. They reported that the suggested combined model can excellently identify the behaviors of underwater acoustic signals and classified them into their appropriate frequencies.

It is clear evidence that the decomposition framework has been lately utilized in studying time series in many areas, including exchange rates, climates, energy consumption, passenger travel movements, among others. Only a few research, however, exist on predicting commodity market futures prices utilizing this novel concept, which has created a gap in the existing literature. In this study, we propose models combined with the decomposition concept to forecast three commodities futures markets prices, namely corn, the most consumable food from agricultural products, crude oil, the main source of energy globally, and gold, the most fascinated metal from industrial metal across commodity market prices. This work presents a neural network predicting model built on EMD and VMD and the EMD-Granger causality test in time-frequency analysis to investigate the causal relationships among commodity markets futures prices series. The EMD and VMD methods were used to generate a series of combined models, namely, the EMD-BPNN, EMD-ARIMA, VMD-ARIMA, and VMD-BPNN. The data pre-treatment effect of EMD and VMD techniques, therefore, is horizontally compared using the three traditional criteria performance measures: root mean square error (RMSE), mean absolute error and mean absolute percentage error (MAPE). We also employed the novel DM test to compare the predicting performance of the suggested models. From this approach, it was established that the combined BPNN model and ARIMA model were superior to the single models.

B. HIGHLIGHTS OF THE STUDY
The key elements of this work are:

- There is causal relationship among corn, crude oil and gold futures prices market series.
- The data analysis shows that models combined with the decomposition methods predict commodity futures prices series better than models without a decomposition approach.
- Another empirical finding is that decomposition improves forecasting ability of BPNN and ARIMA.
- VMD is more suitable for the prices data pre-treatment, since it raises forecasting precision.
- Finally, VMD-ARIMA is suitable in predicting corn futures prices series. EMD-ARIMA is the best forecasting model for crude oil price series, while BPNN is the ideal model for predicting gold price series.

C. DATA
This section of the work deals with the data choice, descriptive properties of employed data, data pre-processing, and step-by-step presentation of the experiment. The data used

TABLE 1. Descriptive statistics of the three commodities.

Commodity	Mean	Std dev	Skew	Kurt.	JB	Min	Max
Corn	3.80	0.58	2.69	11.98	5830.30	3.02	7.53
Crude oil	52.80	10.62	-0.61	4.05	137.17	10.01	76.41
Gold	1429 .00	232.8 9	0.99	2.59	215.66	1128	2069

TABLE 2. Time and sample size of the three commodities futures prices.

Commodity	Time	Sample size	Training	Testing
Corn	2016-2021	1277	1022	255
Crude oil	2016-2021	1022	1022	255
Gold	2016-2021	1277	1022	255

in the empirical study was daily market futures prices of corn, crude oil, and gold, as presented in Table 1, Table 2 and Figure 1-3.

Bloomberg commodities index is regarded as one of the quality price index for international commodity stock markets. Daily spot market price of crude oil, corn, and gold was employed in this study, which consists of 1277 data points from the period 1st May, 2016 to 31st April, 2021, obtainable from http: www.bloomberg.com.

The corn and gold price series are positively skewed, which indicates that the two commodities price series have a right tail distribution. The crude is negatively skewed, which suggest that the price series of crude oil have a left tail distribution. These observations are validated by the minimum and the maximum values of the data points and the time series graphs of the three commodities in Figure 1, Figure 2 and Figure 3 respectively. All the price data of the above-stated commodities are leptokurtic. These characteristics are substantiated by the kurtosis of 11.98, 4.05 and 2.59 respectively. The soaring Jarque-Bera test statistics implies the price data of the aforementioned commodities are not normally distributed. Twenty percent (20%) of each data was used as the test in forecasting the commodity futures prices.

II. TESTING NONLINEARITY IN THE DAILY COMMODITY PRICES
Studies have shown that commodity price series is nonlinear. This could affect the type of a model to be used to cater for this behavior in the data. It is imperative to check the presence of nonlinearities in the price series. Several methods exist in the literature to examine the existence of nonlinearity in a given data, but we employed two simplest and flexible approaches, particularly Keenan test and Tsay test which have ability to detect the memory effects to prevent multicollinearity in the data.

A. KEENAN TEST FOR NONLINEARITY
In testing nonlinearity in financial data, [59] proposed a non-linearity test in discovering the existence of nonlinearity in data series under the general hypothesis process as:

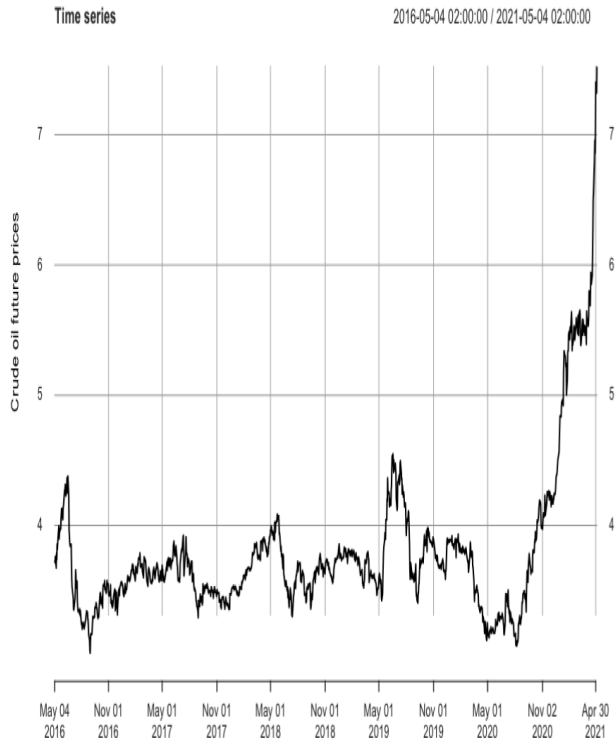$$\begin{cases} H_0 : linearity \\ H_1 : nonlinearity \end{cases}$$

FIGURE 1. Futures prices series of corn (2016–2021).

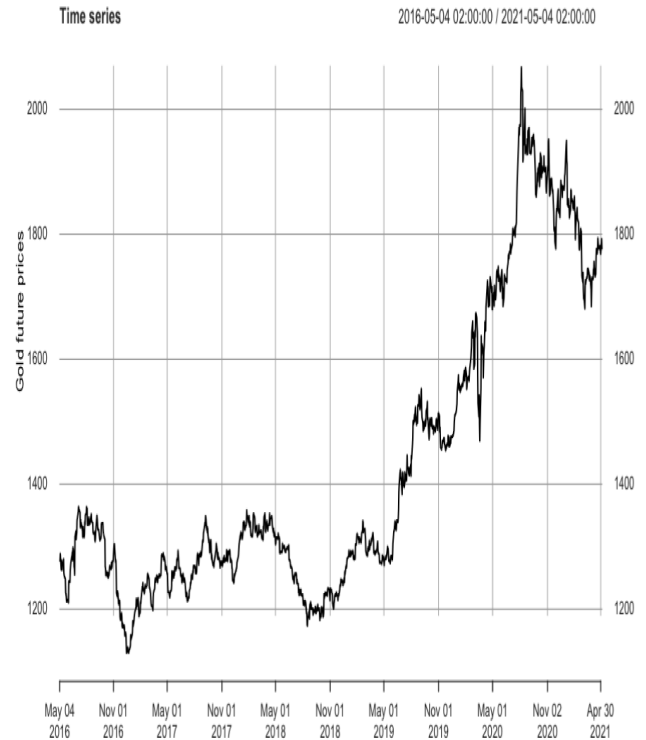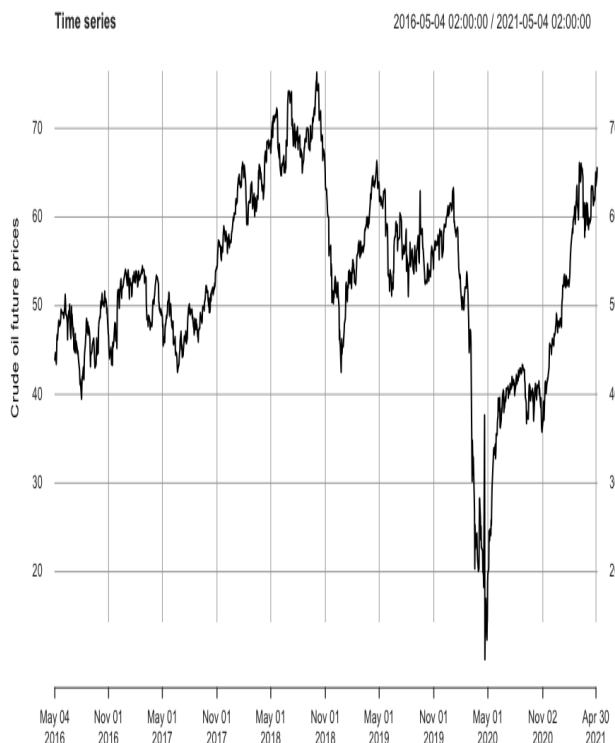**FIGURE 2.** Futures prices series of crude oil (2016–2021).

We follow [60] in presenting Keenan test. We utilized Akaike information criterion (AIC) to describe k, the autoregressive

FIGURE 3. Futures prices series of gold (2016–2021).

order under H_0 that the process is linear. The Keenan test is stemmed from second-order Volterra expansion. The Volterra and Taylor process are identical in principles. Volterra expansion is good for modeling nonlinear time series.

Keenan test conceivably approximated as:

$$q_t = \mu + \sum_{i=-\infty}^{\infty} \theta_i \delta_{t-i} + \sum_{i,j=-\infty}^{\infty} \theta_{i,j} \delta_{t-i} \delta_{t-j}$$
$$+ \sum_{i,j,k=-\infty}^{\infty} \theta_{ijk} \delta_{t-i} \delta_{t-j} \delta_{t-k} + \dots, \quad (1)$$

where δ_t, $-\infty < t < \infty$
are i.i.d. variables and zero mean. $q_1, \dots, q_n$
depicts the observations.
The procedure q_t is linear if

$$\sum_{i=-\infty}^{\infty} \theta_i \delta_{t-i} + \sum_{i,j=-\infty}^{\infty} \theta_{i,j} \delta_{t-i} \delta_{t-j} = 0$$

Conversely, [59] pointed out another systematic way of deducing Keenan test as:

$$q_t = \theta + \psi_1 q_{t-1} + \dots + \psi_l q_{t-l}$$
$$+ exp[\eta(\sum_{j=1}^{l} \psi_j q_{t-j})^2] + \delta_t, \quad (2)$$

where the mean of δ_t is zero with a fixed variance. If the coefficient of regression, $\eta = 0$, then the exponent term

turns to1 and it can be contained in the intercept such that the former model turns to autoregressive model AR_m. If the coefficient of the regression, $\eta \neq 0$, then the prior model is said to be nonlinear. By expanding the term $exp(x) \approx 1 + x$, which is also true for small quantity of x, it can be observed that for slight η, q_t approaches a quadratic AR model:

$$q_t = \theta + 1 + \psi_1 q_{t-1} + \ldots + \psi_l Y_{t-l} + \eta\{(\sum_{j=1}^{l} \psi_j q_{t-j})^2\} + \delta_t \quad (3)$$

In 1985, [61] pointed out the limitations of testing for nonlinearity using Keenan's test as less efficient: still, it is good in discovering nonlinearity patterns in the time series in the form of square approximating linear conditional mean function. The test statistic:

$$P = \eta^2 (\frac{k - 2l - 2}{rss - \eta^2}), \quad (4)$$

where P follows F-distribution with degrees of freedom 5 and $(k - 2l - 2)$.

B. TSAY TEST FOR NONLINEARITY
Owing to the limitations of Keenan test, [61] introduced another nonlinearity test as an improvement of the Keenan test. Furthermore, our presentation follows that of [60]. The Tsay test improved the Keenan's method by changing the term

$$\eta\{(\sum_{j-1}^{l} \phi_j q_{t-j})^2\} \text{ to } exp$$

$$+ (\varsigma_{1,1} q_{t-1}^2 \varsigma_{1,2} Y_{t-1} q_{t-2} + \ldots + \varsigma_{1,l} Y_{t-l} + \varsigma_{2,2} q_{t-2}^2$$
$$+ q_{2,3} q_{t-2} Y_{t-3} + \ldots + \varsigma_{2,l} q_{t-2} q_{t-l} + \ldots + \varsigma_{l-1,l-1} q_{t-l+1}$$
$$+ \varsigma_{l-1,l} q_{t-l+1} q_{t-l} + \varsigma_{l,l} q_{t-l}^2 + \delta_t.$$

By approximation, the nonlinear model approaches a quadratic AR model with an unconstrained coefficients of the quadratic terms. The Tsay test follows the quadratic regression:

$$q_t = \theta_0 + \phi_1 q_{t-1} + \ldots + \phi_l q_{t-l}$$
$$+ \varsigma_{1,2} q_{t-1}^2 + \varsigma_{1,2} q_{t-1} q_{t-2} + \ldots + \varsigma_{1,l} q_{t-1} q_{t-l}$$
$$+ \varsigma_{2,2} q_{t-2}^2 + \varsigma_{2,3} q_{t-2} q_{t-3} + \ldots \varsigma_{2,l} q_{t-2} q_{t-l} + \ldots$$
$$+ \varsigma_{l-1,l-1} q_{t-l+1}^2 + \varsigma_{l-1,l} q_{t-l+1} q_{t-l+1} + \varsigma_{l,l} q_{t-l}^2 + \delta_t \quad (5)$$

and test if all

$$l(\frac{l+1}{2}) \text{ coefficients } \zeta_{ij} = 0.$$

C. NONLINEARITY TEST RESULTS
Table 3 outlines the outcomes of nonlinearity test of the three commodities. Both Keenan and Tsay tests revealed that the daily commodity price series data is nonlinear and this might be due to economic forces. To avert the nonlinearity characteristics in the commodity future price series, this

TABLE 3. Nonlinearity test results of the three commodities price series.

	Keen test	
	Test statistics	p-value
corn	23.3396	1.522666e-06
crude oil	2.763451	0.09669837
gold	0.9615094	0.3269932
	Tsay test	
corn	28.97	8.733e-08
crude oil	3.037	3.114e-42
gold	4.233	0.03984

TABLE 4. ADF test results.

	Test statistic	p-value
Corn	1.8372	0.99
Crude oil	-2.2951	0.4534
Gold	-1.7923	0.6662

present study suggests decomposition based models approach to study commodity futures prices fluctuation of corn, crude oil and gold.

D. STATIONARITY TEST
We further conducted stationarity test in the price series of the three commodities. Table 4 presents the unit root test of the three commodities. The ADF test revealed that the corn, crude oil and gold futures prices data are not stationary. Nonstationary characteristic exhibited by these commodities price series indicated models that can deal with nonstationary is required for any reliable estimates, interpretations and decision making.

III. METHODOLOGY
A. EMPIRICAL MODE DECOMPOSITION (EMD) PROCESS
In search for understanding the non-linearity and non-stationarity in the time series, [28] proposed EMD as data pre-processing tool to decompose signals into fundamental units, IMF, that is derived from the actual data. The EMD does not need a priori basis functions. It is a resilient and adaptive method in studying non-linear and non-stationary data, since it extracts the signals from the data itself. It overcomes the drawbacks of the full frequency content of the Hilbert transform. The EMD is capable in revealing the hidden signals embedded in the actual data, and represents each hidden signal as an IMF.

EMD is a typical data-driven decomposition approach and the IMFs are extracted out of the data itself [28]. As specified by [28], the IMF extracted from the EMD process must fulfill two basic principles:
- In the actual data point, the number of extrema and the number of zero-crossings must either equal or differ at most by one.
- At any period, the mean value of the envelope is specified by local maxima and the envelope specified by the local minima is zero.

The above stated assumptions guarantee that the derived IMF is a harmonic function and carries real facts about the signal associated with the formation of the investigation of the

non-stationary input signal, $v(t)$. At the same time, the IMFs are not fixed and orthogonal to each other, but are flexible and based on the kind of basic signal. The process of obtaining the IMFs is defined as a sifting process.

We follow [42] in describing the EMD process:

(a) identify the maxima and minima of the prices data and represent it as $v(t)$;

(b) use cubic spline interpolation to create the upper and lower envelopes, and;

(c) calculate the mean of the two envelopes using the formula:

$$h(t) = \frac{e_{min(t)} + e_{max(t)}}{2} \qquad (6)$$

(d) subtract the envelope mean, $h(t)$ from the price series, $v(t)$ to obtain

$$d(t) = v(t) - h(t) \qquad (7)$$

(e) verify the characteristics of $d(t)$;

- If $d(t)$ satisfy the conditions of an IMF, we denoted $d(t)$ as i^{th} IMF and replaced $v(t)$ with residual

$$r(t) = v(t) - d(t) \qquad (8)$$

The ith IMF is denoted by $c_i(t)$ and the $c_i(t)$ is called its index;

- If $d(t)$ does not satisfy an IMF conditions, replaced $v(t)$ with $d(t)$.

(f) Repeat steps (a) to (e) until the residuals become either a constant, a monotonic function or have only one extremum. For information about stopping conditions, refer to the work of [42]. Therefore, the commodity price series, $v(t)$ at the end of EMD process can be reconstructed as:

$$v(t) = \sum_{i=1}^{n} c_i(t) + r_n t \qquad (9)$$

where n is IMFs produced, $r_n(t)$ is the last residue, and $c_i(t)$ is the ith IMF.

In the sifting process, c_1 is the first IMF element and contains the finest IMF of the price series, followed by the residue with a longer period, consequently, EMD sorts and classifies the IMFs into their respective frequencies, thus, high and low-frequency modes and residue. In practice, the classification of IMFs is based on the principle defined as 'fin-to-coarse' reconstruction.

EMD has the following attractive properties which make it suitable for decomposing nonlinear data:

1) EMD can break down non-stationary and non-linear signals into individual intrinsic mode function,
2) The decomposition is based on the local characteristic time scale of the data and only extrema take part in the sifting process, hence, it is local, adaptive, effective, and unique 62], and
3) The IMFs decomposed by EMD has an instantaneous frequency based on phase functions, such that Hilbert transform can be applied to the IMFs.

B. VARIATIONAL MODE DECOMPOSITION (VMD)

Despite the advantages of the EMD over other decomposition methods, it is still suffering from a problem called mode mixing and extreme point effect. This is a situation where by one IMF comprising of extensively different scales. To overcome the problem of mode-mixing and extreme point effect in EMD, [48] introduced VMD as mode supported technique to improve EMD. VMD is a non-repetitive signal procedure. It is utilized to break down time series data into individual numbers of band-limited sub-signals, defined as 'modes', y_k, with some sparse features. The decomposed modes can be decreased to a single center called 'pulsation', w_t, and it is accompanied by the decomposition process. We followed the steps below in estimating the bandwidth:

1) Hilbert transform was applied to each decomposed mode y_k, to obtain the center frequency spectrum;
2) Adjust the mode's frequency spectrum to the baseband by variegating the center frequency and the exponential tuned;
3) Evaluate the bandwidth of individual mode, y_k by applying Gaussian smoothness, H^1.

A constrained variational problem can be expressed as: suppose $g(t)$ is the original signal of the data and y_k is the kth of the original signal of the data, then

$$g(t) = \sum_{k=1}^{m} y_k \qquad (10)$$

We reduced the constrained variation as follows:

$$min_{(y_k, \omega_k)} \{ \Sigma_{k=1}^{K} ||\delta_t[(\delta(t) + \frac{j}{\lambda t}) \otimes y_k(t)] e^{-j\omega_k t} ||_2^2 \}$$
$$s.t. \ \Sigma_{k=1}^{K} y_k = g(t) \qquad (11)$$

where $g(t)$ represent the actual series, y_k, denote k^{th} component of the original signal, w_k is the center frequency of y_k, $\delta(t)$ constitute the Dirac distribution, and $\otimes$ act as convolution operator; m is decomposed number of modes and t express the time script. Given the penalty term and Lagrangian multiplier, λ, we can change the constrained problem to unconstrained one as:

$$L(y_k, \omega_k, \lambda) = \ltimes \Sigma_{k=1}^{K} ||\delta_t[(\delta(t) + \frac{1}{\pi t}) \otimes y_k(t)] e^{jw_k t} ||_2^2$$
$$+ ||g(t) - \Sigma_{t=1}^{k} y_k(t)||_2^2$$
$$+ [\lambda(t), g(t) - \Sigma_{k=1}^{k} y_k(t)] \qquad (12)$$

where $\ltimes$ represent constraint stabilizing parameter, L denotes augmented Lagrangian. The augmented Lagrangian L can be estimated in the equation (12) and its associated saddle point in the iterative series. Sub-optimization of L and its minimax level can be secured through the alternate direction method of multipliers (ADMM). ADMM optimization method assumes that upgrading the original signal, y_k, and center frequency, ω_k, in two different directions helps to secure a good VMD results. For a full explanation of ADMM process, see the work of [48].
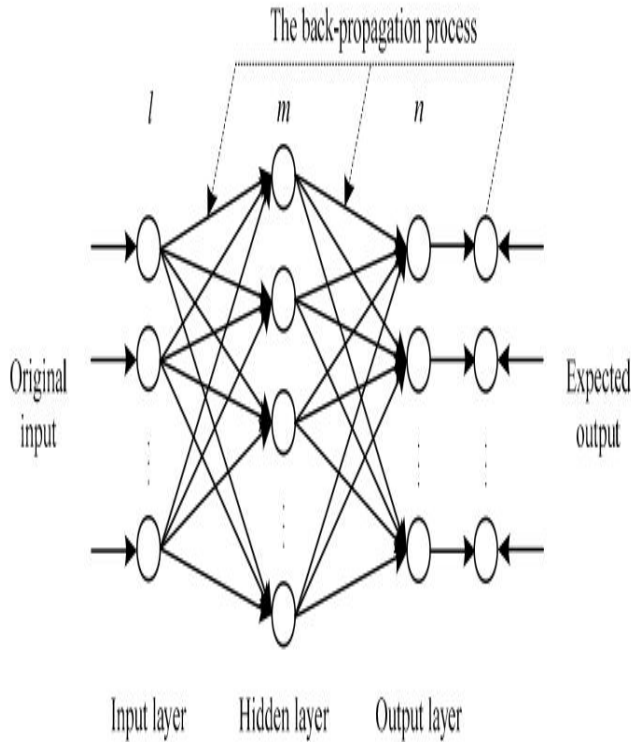
The back-propagation process

FIGURE 4. Three-level back propagation neural network.

The values of y_k and ω can be estimated as:

$$\hat{y}_k^{n+1} = \frac{\hat{f}(\omega) - \Sigma_{i=k}\hat{y}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2 \ltimes (\omega - \omega_k)^2} \qquad (13)$$

$$\omega_t^{n+1} = \frac{\int_0^\infty \omega|\hat{y}_k^{n+1}(\omega)|^2 d_w}{\int_0^\infty |\hat{y}_k^{n+1}(\omega)|^2 d_\omega} \qquad (14)$$

where $\hat{f}(\omega)$, $\hat{y}_i(\omega)$, $\hat{\lambda}(\omega)$ and $\hat{y}_k^{n+1}(\omega)$ are the Fourier transforms of $g(t)$, $y_i(t)$, $\lambda(t)$ and $y_k^{n+1}(t)$ respectively

C. BACK PROPAGATION NEURAL NETWORK (BPNN)

The ANN is a data-driven representative model that can adjust very big non-linear problems to acceptable correctness. Among all the neural networks, Feed-Forward is the most widely used in the commodity market price forecasting, due to its simplicity and numerous studies backing up its efficiency [58]. BPNN is a well-known feed-forward artificial neural network built on the back-propagation process and it has been used in several fields of study. One exceptional edge of BPNN over other models is that it can estimate any non-linear continual function to any desirable level as compared with the conventional statistic methods. In general, a BPNN is made up of one input level, single or additional concealed levels, and one output level. This investigation considered one concealed level, such that a standard three-level, p × p × r BPNN model is obtained, as illustrated in Figure 4.

D. BACK-PROPAGATION PROCESS

We followed [29] in presenting the BPNN algorithm. A standard three-level BPNN contains an input point, single concealed point, and output point. Every point contains several components; the number of components is obtained by using an experimental approach when the BPNN is linked. Each component serves as an input to all the components in the next forward point, and no weight returns to the preceding point output component. Each link has a bias, θ_j, and several weights ω_{ij}, which link component i in the preceding point, denote by v_i, to component j. Hence, we calculated the output, y_j^h in the hidden point and output point using the formula:

$$y_j^h = f(\Sigma_{i=1}^l \omega_{ji} v_i + \theta_j) \qquad (15)$$

where ω_{ji} denotes the connected weight from $i^t h$ input to node to $j^t h$ hidden node, v_i represents the i^{it} input data, θ_j is defined as bias of $j^t h$ concealed neuron, and $f(.)$ represents the non-linear transfer function of the concealed level, which is normally an activation function.

We compute the output of the neural network as:

$$y_k^o = \rho(\Sigma_{j=1}^m \omega_{kj} y_j^k + v_k) \qquad (16)$$

where ω_{kj} denotes the weight linking j^{th} concealed node to k^{th} output node, v_k defines the bias of the kth output neuron, and $\rho(.)$ represents the output point transfer function, and is always linear.

Generally, the BPNN model reduces the mean square error (MSE), E and is estimated as:

$$E = \frac{1}{n} \Sigma_{t=1}^n \Sigma_{k=1}^n (Y_Y - y_k^o)^2 \qquad (17)$$

where n represent the inputs number, Y_k denotes the kth predicted output data.

E. FORECASTING PERFORMANCE EVALUATION CRITERIA FOR COMMODITY PRICES

Generally, several statistical approaches have been used in evaluating commodity futures prices forecasting models in the literature. The most common evaluation criteria used are MAE, RMSE and MAPE. We used the three generally adopted error indices to rate the viability of the suggested methods, in addition to Diebold Mariano (DM) test to differentiate the predicting ability of models in this study, since the traditional evaluation criteria have some setbacks, such as stochastic process, in selecting an ideal model in predicting commodity prices.

The mathematical representation of the three error methods, MAE, RMSE and MAPE, are expressed as:

$$MAE = \frac{1}{n} \Sigma_{i=1}^n |\hat{Y}(i) - Y(i)| \qquad (18)$$

$$RMSE = \sqrt{\frac{1}{n} \Sigma_{i=1}^n (\hat{Y}(i) - Y(i))^2} \qquad (19)$$

$$MAPE = \frac{1}{n} |\frac{\hat{Y}(i) - Y(i)}{Y(i)}| \qquad (20)$$

where n is the sample size, $Y(i)$ is the original dataset, and $\hat{Y}(i)$ equal to the predicting value of the futures prices series.

F. DIEBOLD MARIANO TEST (DM)

Generally, using traditional predicting evaluation of MAE, RMSE and MAPE as forecasting performance precision have some setbacks in choosing the ideal forecasting model. For instance, after estimating the MAE of the predicting model, if the difference between the two models is insignificant, it is not easy to decide at this stage whether the outcome is a result of chance. In reality, a conclusion cannot be reached based on the MAE result. Using a small MAE difference between the models to accept one model, may mean that the best model is rejected because the small differences in the calculation may be a result of stochastic process. To overcome the problems associated with the traditional forecasting performance evaluation criteria, this paper introduced the DM test proposed by [63], which can quantitatively evaluate the predicting accuracy of commodity futures prices models, in selecting an optimal model for predicting each commodity price series.

We followed [64] in presenting DM method. The DM method introduced by [63] can be expressed mathematically as follows:

Let u_n represent the actual series, and $\hat{u}_{n,t}^{h}$ denote the nth contesting h-step predicting series.

Assuming the predicting errors from the nth contesting models are $e_{n,t}^{h}$ ($n = 1, 2, 3, \ldots, k$), where k is the number of predicting models. The h-step predicting errors $e_{n,t}^{h}$, is given by:

$$e_{n,t}^{h} = y_t^{h} - \hat{u}_{n,t}^{h}(n = 1, 2, 3, \ldots, k) \tag{21}$$

The precision of every predict is evaluated using the loss function:

$$S(u_t^{h}, \hat{u}_{n,t}^{h}) = S(e_{n,t}^{h}) \tag{22}$$

In this study, we set, h to 1, and neglected the superscript h in the context below. In practice, several loss functions have been used, and most common loss functions in commodity markets are the SE loss and the AE loss functions.

The squared-error function is given by:

$$S_2(u_t, \hat{u}_{n,t}^{h}) = S_2(e_{n,t}) = \Sigma_{t=1}^{T}(e_{n,t})^2 \tag{23}$$

Absolute-error loss function is expressed as:

$$S_1(u_t, \hat{u}_{n,t}^{h}) = S_1(e_{n,t}) = \Sigma_{t=1}^{T}|e_{n,t}| \tag{24}$$

The two errors, SE and AE, are symmetrical about the origin. Additionally, the SE loss function can severely deal with larger errors.

To evaluate if one predicting model, for instance, the model A predicts better than the model B, then we test for equality accuracy of the two models under the null hypothesis:

$$H_0 : E[S(e_{1,t})] = E[S(e_{2,t})] \tag{25}$$

The alternative hypothesis that one model has superior predicting accuracy to the other model is expressed by:

$$H_1 : E[S(e_{1,t})] \neq E[S(e_{2,t})] \tag{26}$$

The DM method is derived by differentiating the differential loss function, d_t:

$$d_t = S(e_{1,t}) - S(e_{2,t}) \tag{27}$$

The equal predictive accuracy of the null hypothesis is expressed as $H_0 : E[d_t] = 0$. If $\bar{d}$ is the sample mean loss, then, $\bar{d}$ is given by:

$$\bar{d} = \frac{1}{T}\Sigma_{t=1}^{T}[S(e_{1,t}) - S(e_{2,t})] \tag{28}$$

The DM test statistic is expressed as:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{T}}} \tag{29}$$

where $2\pi\hat{f}_d(0)$ represent a constant estimator of the asymptotic variance of $\sqrt{T}d$ and d is normally distributed. The variance is applied on the statistics since the sample loss differentials, d_t, are succeeding correlated for h greater than 1. We reject the H_0 at 5% level if $|DM|$ is greater 1.96, or else, if $|DM|$ less than or equal to 1.96, we fail to reject the H_0, since the DM statistics converges to a nornal distribution. The DM test can help to reveal the interference of the sample stochastic difference, such that optimal predicting model can be identified statistically.

IV. EMPIRICAL RESULTS AND ANALYSIS

This section of the study presents the experimental results and analysis of one day-ahead out-of-sample prediction of corn, crude oil, and gold futures prices in this section, applying the four combined forecasting models- EMD-BPNN, EMD-ARIMA, VMD-BPNN, and VMD-ARIMA- models.

In time series forecasting using the BPNN model, many prior data points are selected as the input to forecast the subsequent one since the predicting accuracy is affected by the input's limit. The ideal limit of the BPNN's input series was ten after a provisional examination of different forecasting results with distinct input limit. Regarding the time series $K_t, t = 1, 2, \ldots, m$, this study utilizes $K_1, K_2, K_3, K_4, K_5, K_6, K_7, K_8, K_9, K_{10}$ to forecast K_{11}; and so on. K_{t+10} could, therefore be predicted by $K_t, K_{t+1}, K_{t+2}, K_{t+3}, K_{t+4}, K_{t+5}, K_{t+6}, K_{t+7}, K_{t+9}$. The principal variables of the BPNN were put as smoothing threshold 0.01%, some nodes 10, hidden number of layers 2, output number 1, and maximum iteration 100. It should be noted that the variables mentioned are estimated through a series of experiments. We maintain this input limit and these variables settings of the predicting model throughout our analysis. We treat the BPNN as the standard model, ARIMA as relative model and compare their predicting accuracy with the four suggested combined models.

TABLE 5. Results of EMD-causality test: Causality test is significant at 0.01 '*' 0.05 '**'. 0.1 '***' level.

	Corn	Crude oil	Gold
Corn		0.069*	0.718
Crude oil	0.014**		0.730
Gold	0.071**	0.005**	
Corn+crude oil			1.00
Corn+gold		0.322	
Crude oil+gold	0.731		

A. EMD-CAUSALITY ANALYSIS

The EMD-Causality analysis was introduced to analyze the causal association among the three commodities- corn, crude oil, and gold- futures. Table 2 shows the causality test results and their respective ρ values. The causal relationship between commodity futures in each row and column rests on the value of ρ, for instance, a ρ of 0.014 indicates an EMD-causal relationship between crude oil and corn at the 5% level of significance. This figure signifies that the crude oil futures could explain the characteristic movement of corn futures. It further suggests that from the knowledge about the crude oil futures market, one could understand the features of corn futures prices' movement. This relationship is the reason the agricultural market prices have been consistently affected by the crude oil market prices. Figures 1 and 2 indicate that crude oil prices go up continuously, thereby increasing corn price or if there was unprecedented corn production; this signifies an EMD-causal relationship between the two commodity futures prices. ρ value of 0.069 indicates that corn futures can also determine the futures of gold prices, however, the combined futures of crude oil and gold at the 5% level have an insignificant impact on corn futures.

In the case of crude oil futures, the gold futures is the EMD-causal of crude oil at the significance level of 0.05. From Table 3, the combined futures prices of gold and corn give no clue in understanding the future movement of crude oil futures since the ρ-value of 0.322 is above the benchmark value of 0.05 at the significance level of 0.05. Eventually, the price of gold is fairly steady in EMD-causal as usually, gold is a kind of commodity that is used as a guard against inflation.

B. DATA PRE-TREATMENT

We utilized the EMD and VMD methods to pre-process corn, crude oil and gold price series. The EMD technique decomposed the actual series of every commodity price series into several IMFs and a residue (RES). There is no way to adjust the number of IMFs produced by the EMD technique for any give sample data. Figure 5 illustrates the procedure of the EMD approach.

Unlike the EMD method, the VMD approach, the number of modes decomposed can be altered to fit the research requirements. Here, a series of tests are performed to choose the optimal number of decompositions for the time series in this research, as illustrated in the fourth part of this study. The VMD procedure is showed in Figure 6.
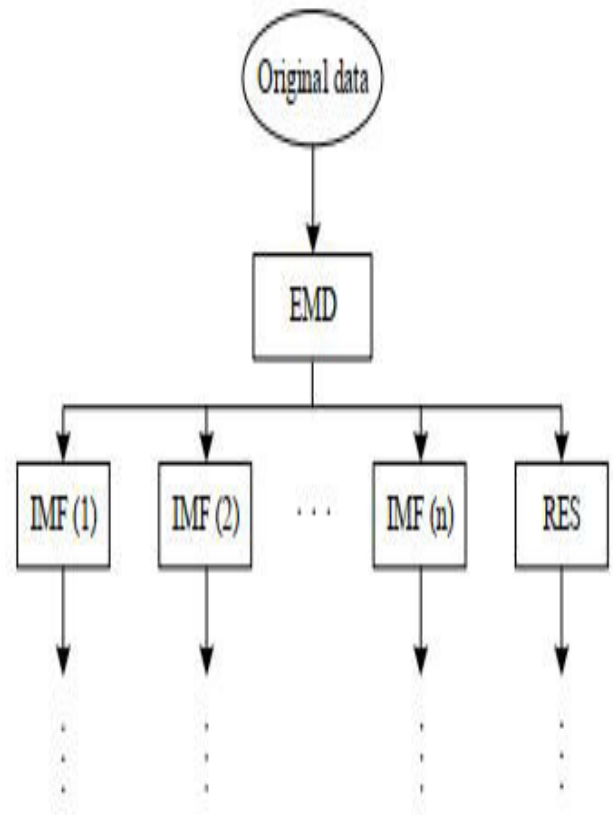

FIGURE 5. EMD procedure.

C. EXPERIMENTAL PROCEDURE

It can be observed from Figure 7 that; this study's experiment procedure involves four steps:

1) price series of every commodity futures were decomposed through EMD and VMD respectively, which produces an aggregate of sub-series;
2) each sub-series is normalized using distinctive linear transformation before the predicting stage;
3) enter all the normalized sub-series into the EMD-BPNN, EMD-ARIMA, VMD-BPNN, and VMD-ARIMA models, producing an array of predictions which are considered and reversed using the normalization process; and
4) add all the predicted values to obtain the final forecast value.

Decomposition Analysis of The Three Commodities:

D. DECOMPOSITION ANALYSIS OF CORN

This part of the work presents the decomposition results of corn futures market prices through EMD and VMD.

The corn futures market prices utilizing the EMD technique generated seven IMFs and one residue, known as IMF1, IMF2, ..., IMF7. Figure 8 indicates the IMFs and the residue of corn prices series. The IMFs were grouped in the order in which they were derived, from highest to lowest frequency component. The residue is represented by the last diagram in each decomposition curve. These IMFs represent the trend,
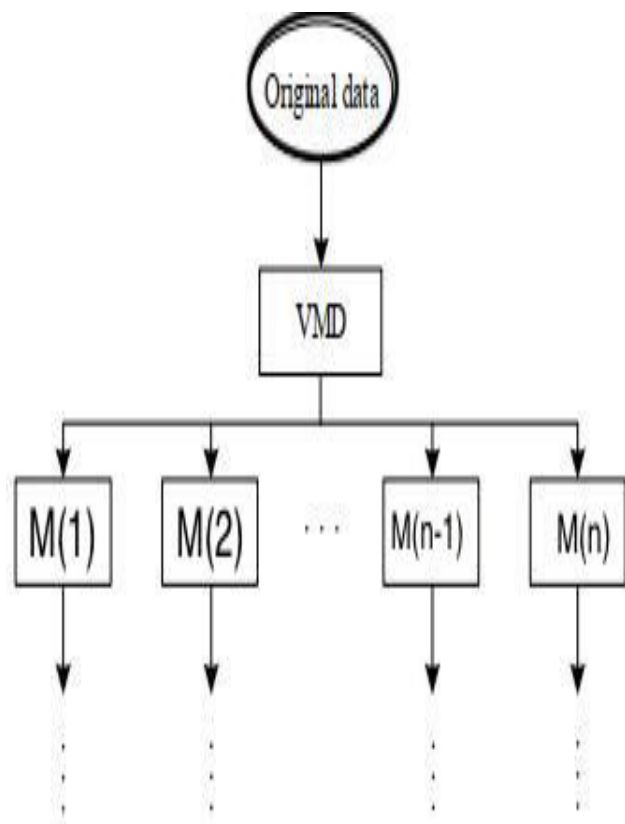
FIGURE 6. VMD procedure.

FIGURE 7. Basic structure of proposed combine model.

market price fluctuations, and significant events or seasonality components of the price sequence.

We also subjected the corn data price series to VMD method and decomposed it into eight distinct band-limited sub-signals- modes and aggregates- as shown in Figure 9. This study analyzed the decomposition result of eight discrete modes - m1, m2, . . . , m8- thus, from lowest to the highest frequency; the process gave eight combined models forecasting accuracy as showed in Figure 9.

E. COMPARATIVE ANALYSIS OF CORN FUTURES SERIES

From the results of the two decomposition techniques in Figure 8 and 9, this study utilized the BPNN model to predict the last 20% of the corn price series, namely, 255 forecasting values in a total of sub-series and added up to produce 255 forecasting values of corn futures prices. The BPNN model was fitted without decomposition techniques as a standard model to test the two decompositions' capability. We formed four combined models, namely, EMD-BPNN, VMD-BPNN, EMD-ARIMA, and VMD-ARIMA.

Subsequently, the ARIMA model was fitted and considered as the comparative model to evaluate the robustness of the predicting ability of the BPNN model. The comparative analysis of one-day ahead out-sample predicting results of six models are presented in Figure 11. The models' predictive capability is assessed using three statistical measures - MAE, RMSE, and MAPE - as illustrated in Table 4.
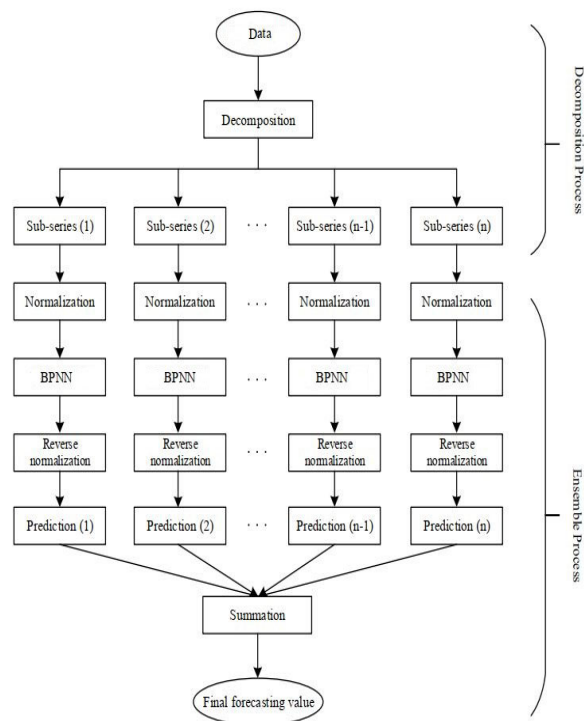
It is clear from Table 6 and Figure 10 that, the VMD-ARIMA model outperformed all the proposed forecasting models, namely EMD-BPNN, EMD-ARIMA, VMD-BPNN, BPNN, and ARIMA, in respect of the values of MAE, RMSE, and MAPE, which are 0.3566, 0.5886 and 0.0954 for the VMD-ARIMA model. This comparison signified that the decomposition techniques suggested in this study can boost the predictability precision of the ARIMA model of corn futures prices series. The VMD-ARIMA model outperformed all models combined with EMD techniques, which means the VMD approach has an edge over the EMD in terms of data pre-processing. The VMD-ARIMA model has the smallest predictive error value as compared to VMD-BPNN, EMD-BPNN, and EMD-ARIMA in terms of the three criteria performance measures. It can also be deduced that the VMD-ARIMA has the most reduced MAE, RMSE, and MAPE values from a pure data perspective. From Table 6 and Figure 10, the comparison between the BPNN model and the ARIMA model, with regard to MAE, RMSE, and MAPE, the BPNN model has a smaller error value than ARIMA; this means that the BPNN model has proved to be quite versatile. It can be further deduced that the EMD did not improve predictive ability of BPNN for the MAE, RMSE and MAPE.

F. PAIRWISE COMPARISON OF SUGGESTED MODELS OF CORN BY DM TEST: TWO SIDED

This section compares the predicting capability of the six suggested models by using the DM test to select the optimal
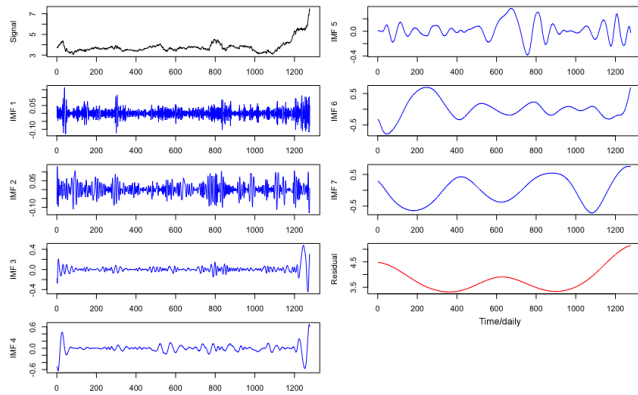
FIGURE 8. IMF and residue of daily corn price series obtained by EMD (2016–2021).
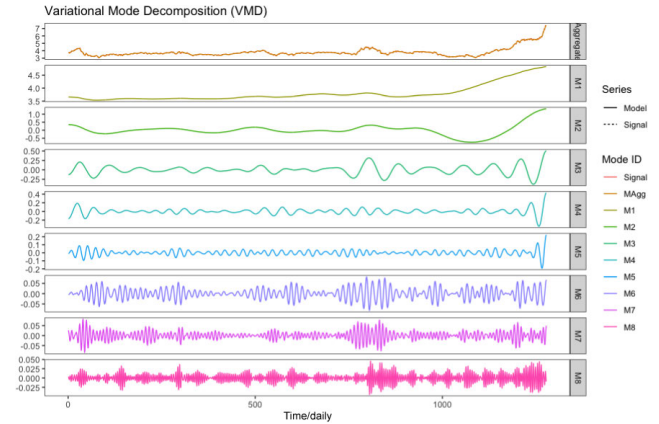

FIGURE 9. Mode of daily corn price series obtained by VMD (2016–2021).

model in forecasting corn price series. Generally, MAE, RMSE, and MAPE as forecasting performance evaluation criteria, have peculiar limitations, such as stochastic differences in selecting the optimal predicting model. The classical indices normally provide false results if the impact of stochastic difference is powerful, hence, in this study, we applied the DM test as a new evaluation criterion in choosing the optimal model in forecasting commodities futures prices series based on a statistical hypothesis test.

We followed [59] in analyzing the forecasting capabilities of the suggested models. The null hypothesis is that, the two models have the same level of predicting precision. An alternative ''two sided'', hypothesis is that, the two models have different levels of predicting precision. If the DM-value is greater than 1.96 it means that model 1 and model 2 have different levels of predicting precision. If the DM-value is less than 1.96, then the two models have the same levels of predicting accuracy. If the DM statistic is positive, it suggests that the first model is more efficient than the second mode, while a negative DM value means the second model is superior to the first model. The predicting comparison of each and every two predicting models is presented in Table 7. According to DM test results in terms of absolute-error loss, the absolute value of the DM test is 9.219 which is exceeding 1.96, the H_0 is discarded at the 5% level of significance, which is to say that, there are remarkable differences and the predicting precision of the VMD-ARIMA model is ahead of EMD-ARIMA model. In addition, from the DM results based on square-error loss, the absolute of 4.542 is more than 1.96, we accept the alternative hypothesis at the 5% level of significance, and say that, there is remarkable differences between the two models and predicting accuracy of the VMD-ARIMA model is higher than that of the EMD-ARIMA model. In the same manner, from Table 7, the DM test with respect to percentage-error loss, the absolute value of 11.652 is bigger than 1.96, the null hypothesis is turned down at the 5% significance level, hence, the VMD-ARIMA and EMD-ARIMA models have a different predicting capability, and that VMD-ARIMA model has high forecasting precision than the EMD-ARIMA model.

Similarly, the predictive analysis of the BPNN model and ARIMA model from Table 7, the three DM tests by absolute-error loss, square-error loss and percentage-error loss estimate that the BPNN model has efficient predicting performance accuracy over the ARIMA model. The predicting comparison of EMD-BPNN and ARIMA models, the DM test with respect to absolute-error loss, percentage-error loss, and percentage-error loss, the observed difference between the predicting ability of EMD-BPNN model and ARIMA is significant since the DM values of 3.704, 5.313 and 4.323 is greater than 1.96, indicating that EMD-BPNN model has high predicting performance than ARIMA model. The predicting performance of the VMD-BPNN model and the BPNN model is insignificant and might be due to stochastic disturbance. In addition, the comparison between VMD-ARIMA model and BPNN model indicates that the forecasting capability of the two models are the same and the differences might be stochastic process in the data.

Finally, the rest of predicting comparison of the models are summarised in Table 7. The VMD-ARIMA model is more robust in predicting corn futures prices series because it improves predicting accuracy, such as the MAPE, by order of magnitude contrarily to the EMD-BPNN, EMD-ARIMA, and ARIMA models. The VMD-based model performed better than other combined models due to several reasons:

1) VMD computes the connected signal through Hilbert transform by searching for a unilateral frequency spectrum;
2) VMD method is good for sampling and noisy signals such as agricultural commodity future price; and
3) VMD uses the bandwidth estimator approach through Gaussian smoothness to demodulate signal in decomposing time series data.

In general, VMD is strongly connected to the Wiener filter, making this data pre-processing technique more efficient to deal with the signals' noise [47]. VMD is more robust in capturing both short and long signal variation than other decomposition approaches. Figure 11 illustrates one-day ahead forecasting of the proposed models of corn.

TABLE 6. Predicting performance evaluation of suggested models of corn.

Model	Criteria		
	MAE	RMSE	MAPE
BPNN	0.38748	0.66049	0.101664
EMD-BPNN	3.76884	4.00845	12.59252
EMD-ARIMA	1.033128	1.189707	0.2072793
VMD-BPNN	0.3902415	0.6051587	0.1016804
VMD-ARIMA	0.3565786	0.5886037	0.09541595
ARIMA	3.721718	3.774212	49.13432

G. DECOMPOSITION ANALYSIS OF CRUDE OIL

Likewise, the crude oil price data was decomposed through EMD and VMD techniques. The graphical representations of the two methods are given in Figure 12 and 13, separately. With the decomposition results, the two suggested decomposition techniques were combined to the BPNN and the ARIMA models to form hybrid models to forecast the crude oil futures prices ranging from May 2016 to April 2021, using BPNN as a standard model and ARIMA as the relative model.

The EMD technique automatically decomposed the price series of crude oil futures into eight IMFs, IMF1, IMF2, ..., IMF8, and one residue, as presented in Figure 12. With the VMD method, the number of modes were altered to suit the study needs. A series of tests were performed to choose the ideal modes for the forecasting in this study. The VMD curves of crude oil are shown in Figure 13.

H. COMPARATIVE ANALYSIS OF CRUDE OIL

This part of the study presents the comparative and forecasting analysis of daily crude oil price series utilizing the suggested combined models. With reference to the decomposition results, we employed the combined models to predict the crude oil futures prices from 2016-2021, which constitute 1277 observations. The BPNN model was used to forecast the last 20% of the crude oil price series without decomposition techniques, obtaining 255 predicting values in the total of each sub-series. A total of 255 forecasting values of crude oil futures prices, are showed in Figure 15.

The BPNN model emerged as the best-predicted model compared with the EMD-BPNN, VMD-BPNN, EMD-ARIMA, VMD-ARIMA, and ARIMA models, in respect of forecasting performance evaluation criterion MAE, as indicated in Table 8. For the case of MAE, the order of the six models, in ascending order, is BPNN (8.15346), VMD-ARIMA (8.30159), EMD-ARIMA (8.36213), VMD-BPNN (9.23340), EMD-BPNN (51.60599) and ARIMA (23.70603). Using RMSE as a forecasting performance evaluation criterion, the VMD-ARIMA model has high forecasting ability than other hybrid models. With reference to RMSE, the order of the models is VMD-ARIMA (10.69119), BPNN (10.77160), EMD-ARIMA (10.80187), VMD-BPNN (11.61286), ARIMA (25.49950) and EMD-ARIMA (53.93394). Similarly, according to MAPE, the best model is EMD-ARIMA; from the MAPE, the order of the models is as follows: VMD-ARIMA (0.15321%),

TABLE 7. DM test of suggested models of corn: two sided.

Model	MAE		RMSE		MAPE	
	DM value	p-value	DM value	p-value	DM value	p-value
EMD-BPNN*VMD-BPNN	23.466	2.2e-16	10.405	2.2e-16	26.244	2.2e-16
EMD-BPNN*EMD-ARIMA	20.402	2.2e-16	10.251	2.2e-16	23.56	2.2e-16
EMD-BPNN*VMD-ARIMA	23.514	2.2e-16	10.41	2.2e-16	26.28	2.2e-16
EMD-BPNN*BPNN	23.847	2.2e-16	10.484	2.2e-16	26.243	2.2e-16
EMD-BPNN*ARIMA	3.704	0.00026	5.313	2.357e-07	4.323	2.206e-05
VMD-BPNN*EMD-ARIMA	-9.113	2.2e-16	-4.855	2.11e-06	-11.448	2.2e-16
VMD-BPNN*VMD-ARIMA	1.4277	0.155	-0.162	0.871	2.337	0.020
VMD-BPNN*BPNN	-1.469	0.143	-1.931	0.0546	0.142	0.887
VMD-BPNN*ARIMA	-39.632	2.2e-16	-11.886	2.2e-16	-549.06	2.2e-16
VMD-ARIMA*EMD-ARIMA	9.219	2.2e-16	4.5422	8.608e-06	11.652	2.2e-16
EMD-ARIMA*ARIMA	-29.419	2.2e-16	-11.509	2.2e-16	-93.931	2.2e-16
EMD-ARIMA*BPNN	6.971	2.706e-11	1.144	0.254	11.149	2.2e-16
VMD-ARIMA*ARIMA	-39.928	2.2e-16	-11.903	2.2e-16	-636.49	2.2e-16
VMD-ARIMA*BPNN	-1.932	0.05452	-1.954	0.052	-1.711	0.088
ARIMA*BPNN	42.831	2.2e-16	12.193	2.2e-16	508.77	2.2e-16

TABLE 8. Forecasting performance evaluation of suggested models of crude oil.

Model	Criteria		
	MAE	RMSE	MAPE
BPNN	8.15346	10.77160	0.15455
EMD-BPNN	51.60599	53.93394	16.40526
EMD-ARIMA	8.36213	10.80187	0.15321
VMD-BPNN	9.23340	11.61286	0.17959
VMD-ARIMA	8.30159	10.69119	0.15587
ARIMA	23.70603	25.49950	0.79131

BPNN (0.15455%), VMD-ARIMA (0.15587%), VMD-BPNN (0.17959%), ARIMA (0.79131%) and EMD-PBNN (16.40526%). This brought about a debate, as to which model is optimal in forecasting crude oil price series. We performed DM test to evaluate the accuracy of the selected models from the three predicting estimation criteria to choose the best predicted method. The errors of the suggested models are presented in Figure 14.

I. PAIRWISE COMPARISON OF SUGGESTED MODELS OF CRUDE OIL BASED ON DM TEST: TWO SIDED

From Table 9, the DM test about the AE loss, shown that the DM-AE of 26.61 is more than 1.96, therefore the H_0 is abandoned at the 5% level of significance, hence, the
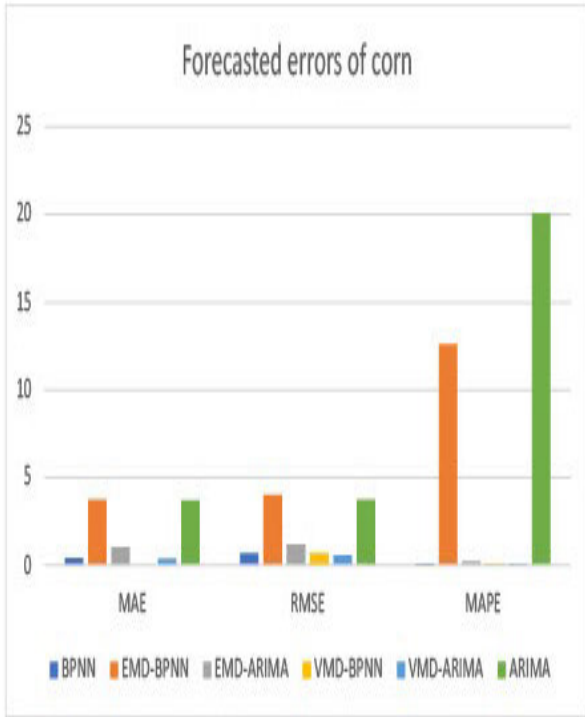
FIGURE 10. Graphical representation of errors of suggested models of corn (2016–2021).
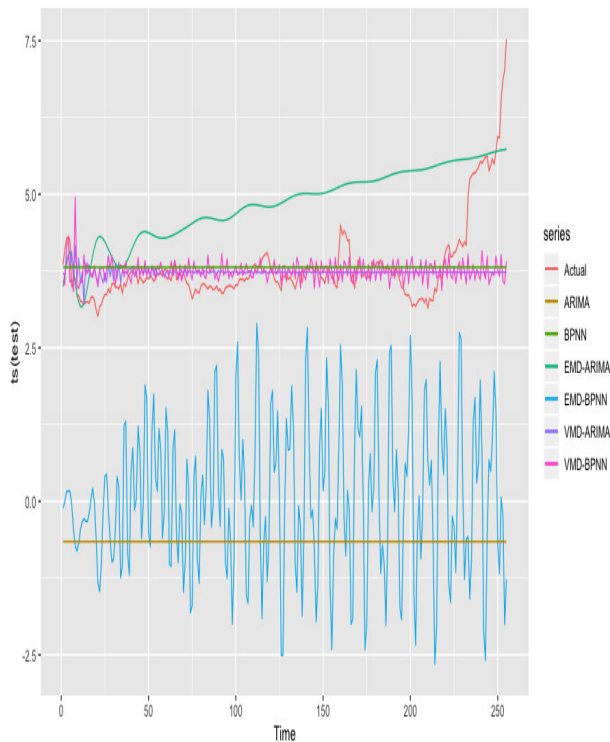

FIGURE 11. A day-ahead out of sample predicting results of suggested models of corn (2016–2021).

predicting performance ability of the VMD-BPNN model is superior to the EMD-BPNN model. Similarly, according to
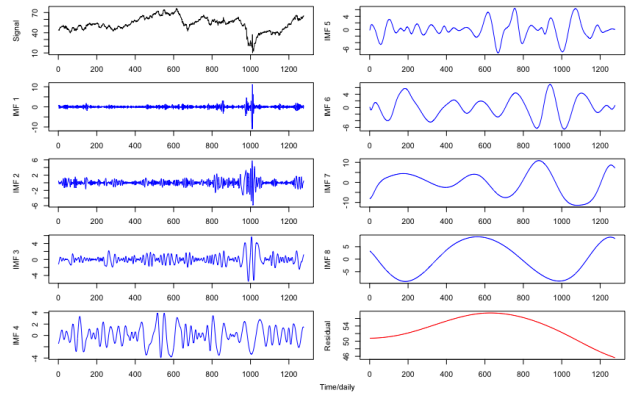

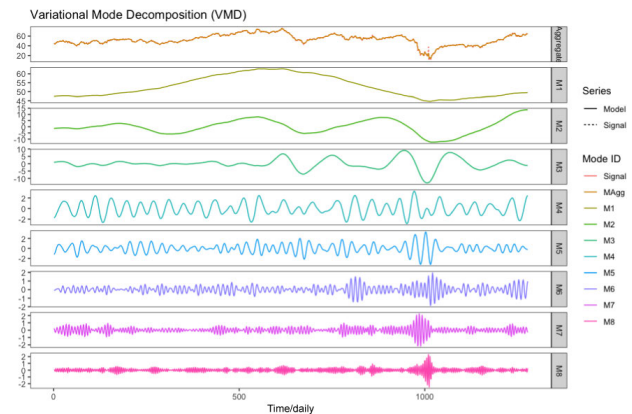**FIGURE 12.** IMF and residue of daily crude oil price series obtained by EMD (2016–2021).

FIGURE 13. Mode of daily crude oil price series obtained by VMD (2016–2021).

SE loss and PE loss, the DM-SE and DM-PE of 14.80 and 16.798 are greater than 1.96, as shown in Table 9, indicating that the VMD-BPNN model has greater predicting precision than the EMD-BPNN model. Equivalently, the predicting comparison of EMD-BPNN and EMD-ARIMA in Table 9, all the DM test by AE loss, SE loss, and PE loss estimate indicate that there is a significant predicting performance of EMD-BPNN and EMD-ARIMA, and that EMD-ARIMA has greater forecasting ability than EMD-BPNN, since DM values of 26.316, 14.80 and 17.188, in terms of DM-AE, DM-SE, and DM-PE are greater than the tabulated value.

The DM test in respect of the AE loss, SE loss and PE loss evaluate that, there is a significant forecasting between the EMD-BPNN model and the VMD-ARIMA model, and therefore, VMD-ARIMA model forecasting ability is greater than the EMD-BPNN model. According to the DM test with respect to DM-AE, DM-SE and DM-PE losses, indicate no remarkable difference in the predictability of the VMD-BPNN and the BPNN model and this might be due to the stochastic process. All the three DM tests, DM-AE loss, DM-SE loss, and DM-PE loss suggest that the predicting performance of the BPNN model is superior to EMD-BPNN. A comparison of the EMD-BPNN and the ARIMA based on the three errors- AE loss, SE loss and PE loss- estimate that the predicting ability of the EMD-BPNN model and the

TABLE 9. Diebold Mariano test: two-sided.

Model	MAE		RMSE		MAPE	
	DM value	p-value	DM value	p-value	DM value	p-value
EMD-BPNN*VMD-BPNN	26.61	2.2e-16	14.8	2.2e-16	16.798	2.2e-16
EMD-BPNN*EMD-ARIMA	26.316	2.2e-16	14.79	2.2e-16	17.188	2.2e-16
EMD-BPNN*VMD-ARIMA	5.8766	1.31e-08	6.9303	3.447e-11	4.2954	2.485e-05
EMD-BPNN*BPNN	26.442	2.2e-16	14.797	2.2e-16	16.917	2.2e-16
EMD-BPNN*ARIMA	24.341	2.2e-16	14.452	2.2e-16	17.816	2.2e-16
VMD-BPNN*EMD-ARIMA	2.5517	0.01131	1.0881	0.2776	-	0.7968 0.25775
VMD-BPNN*VMD-ARIMA	-36.447	2.2e-16	-20.759	2.2e-16	-8.2758	7.28e-15
VMD-BPNN*BPNN	1.1991	0.2316	0.39309	0.6946	0.46112	0.6451
VMD-BPNN*ARIMA	-16.699	2.2e-16	-10.345	2.2e-16	-0.44312	0.6581
EMD-ARIMA*VMD-ARIMA	-35.302	2.2e-16	-20.681	2.2e-16	-8.4249	2.702e-15
EMD-ARIMA*ARIMA	-16.507	2.2e-16	-10.371	2.2e-16	-0.43097	0.6669
EMD-ARIMA*BPNN	0.044000	0.9649	0.078430	0.9375	0.4923	0.6229
VMD-ARIMA*ARIMA	39.557	2.2e-16	21.203	2.2e-16	135.16	2.2e-16
VMD-ARIMA*BPNN	35.705	2.2e-16	20.699	2.2e-16	26.193	2.2e-16
ARIMA*BPNN	16.297	2.2e-16	10.561	2.2e-16	2.6326	0.00899

FIGURE 14. Graphical representation of errors of suggested models of crude oil.

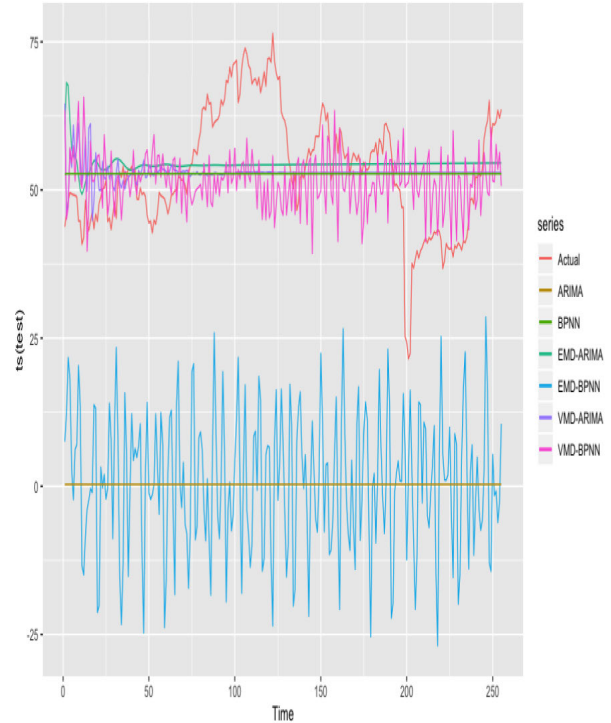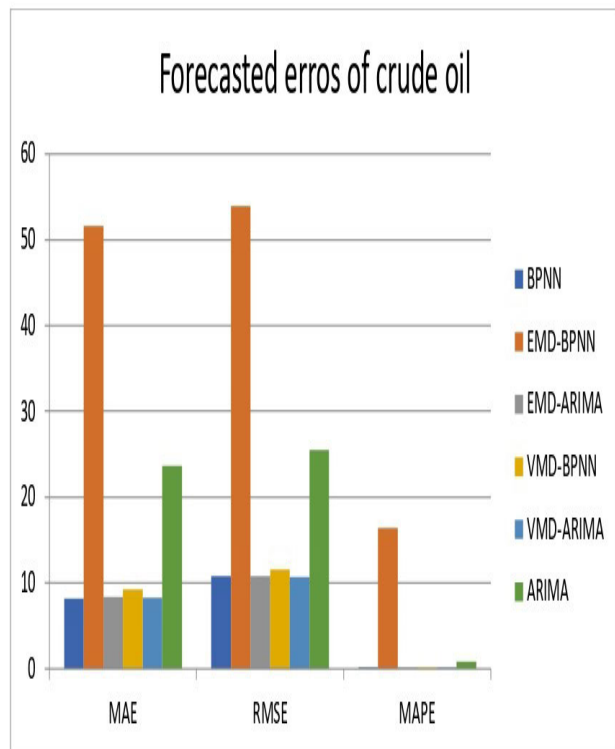ARIMA model is significant and that the ARIMA model has good predicting precision compared to EMD-BPNN model.
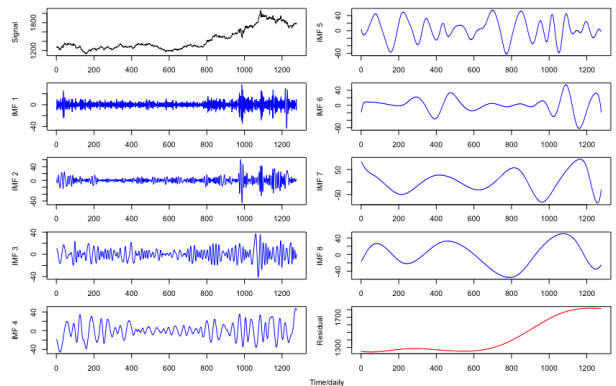

FIGURE 15. A-day-ahead out of sample predicting results of different models of crude oil (2016–2021).

FIGURE 16. IMF and residue of daily gold price series obtained by EMD (2016–2021).

The BPNN model has more desirable predicting capability as compared to ARIMA model based on DM-AE and DM-SE respectively. Overall, we conclude that EMD-ARIMA is the robust forecasting model for the crude oil future price market.

J. DECOMPOSITION ANALYSIS OF GOLD

In the same manner, the EMD and VMD methods were applied to disintegrated the gold futures prices series. The IMFs and the modes derived from the two techniques are presented in Figures 16 and 17. The two suggested decompositions were combined with the BPNN and the ARIMA models to predict 20% of the gold futures prices from April, 2016 to May, 2021, to obtain 255 predicting values.
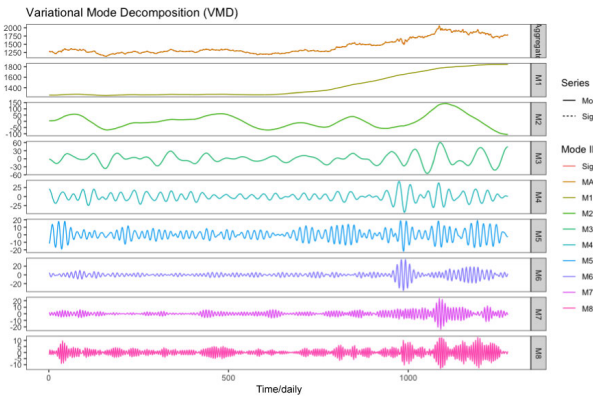
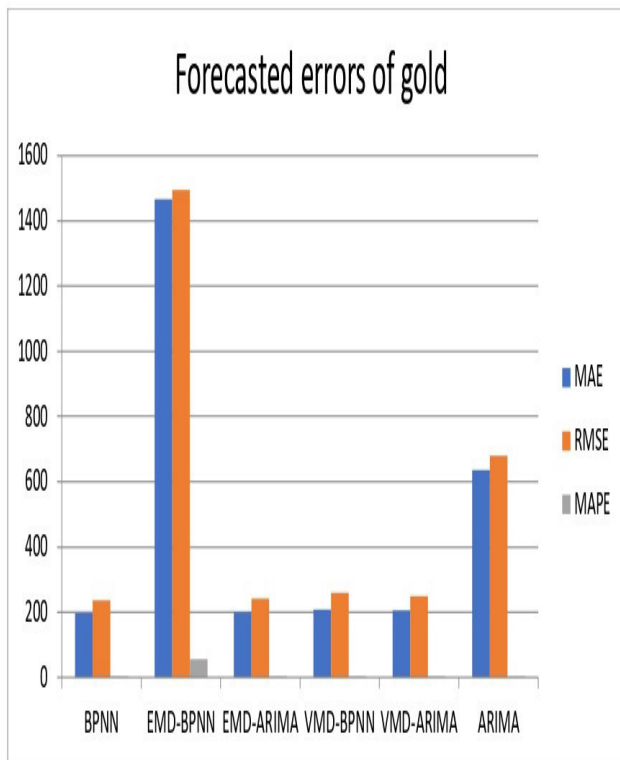**FIGURE 17.** Mode of daily gold price series obtained by VMD (2016–2021).

FIGURE 18. Graphical representation of errors of suggested models of gold.

FIGURE 19. A day ahead out of sample predicting results of different models of gold (2016–2021).

TABLE 10. Predicting performance evaluation of gold.

Model	Criteria		
	MAE	RMSE	MAPE
BPNN	197.21140	236.53266	0.13861
EMD-BPNN	1467.82700	1495.74200	55.94444
EMD-ARIMA	199.36100	241.88060	0.14021
VMD-BPNN	208.93590	259.22930	0.14664
VMD-ARIMA	205.37090	249.35150	0.14368
ARIMA	636.58430	679.01130	0.80577

The EMD approach produced eight decomposed IMFs and one residual sub-series of the price data series of gold future, presented in Figure 16. The VMD approach broke down the gold price series into eight modes, as shown in Figure 17.

K. COMPARATIVE ANALYSIS OF GOLD

This section presents the comparative analysis of the gold prices series utilizing EMD and VMD methods. Figure 16 and 17 present the IMFs, residue and modes obtained through EMD and VMD, respectively. The experimental results of forecasting the gold futures prices using the suggested combined models are presented in Table 10. Figure 18 shows a graphical representation of error measures of different modes. One-day-ahead out-sample forecasting

of gold futures prices of different modes is presented in Figure 19.

A hybrid-model technique was used to predict the gold futures prices from 2016 to 2021, which consist of 1277 observations. The BPNN model was used to forecast the latest 20% of the gold price series, obtaining 255 predicting points in a total of each sub-series. A total of 255 forecasting values of gold futures prices, are shown in Figure 19.

Likewise, the experimental results indicated that BPNN outperformed all suggested combined models- EMD-BPNN, EMD-ARIMA, VMDARIMA, VMD-BPNN and ARIMA models- in reference to the three forecasting performance evaluation criteria, as indicated in Table 10 and Figure 18. From Table 10, we can conclude that the empirical result as that of crude oil. The BPNN model emerged as the robust model in predicting the gold futures prices, according to MAE, RMSE, and MAPE. The VMD-ARIMA and EMD-ARIMA models have more satisfactory performance

TABLE 11. Diebold Mariano test: two-sided.

Model	MAE DM value	MAE p-value	RSME DM value	RSME p-value	MAPE DM value	MAPE p-value
EMD-BPNN*VMD-BPNN	41.428,	2.2e-16	19.754	2.2e-16	73.455	2.2e-16
EMD-BPNN*EMD-ARIMA	41.66	2.2e-16	19.753	2.2e-16	74.312	2.2e-16
EMD-BPNN*VMD-ARIMA	2.8361	0.004934	3.7064	0.000258	2.7998	0.0055
EMD-BPNN*BPNN	41.412	2.2e-16	19.752	2.2e-16	74.895	2.2e-16
EMD-BPNN*ARIMA	45.482	2.2e-16	20.323	2.2e-16	58.551	2.2e-16
VMD-BPNN*EMD-ARIMA	3.5306	0.0004921	3.1258	0.00198	3.715	0.0002498
VMD-BPNN*VMD-ARIMA	-48.029	2.2e-16	-21.676	2.2e-16	-559.42	2.2e-16
VMD-BPNN*BPNN	2.7844	0.005766	2.0711	0.03936	2.6956	0.007496
VMD-BPNN*ARIMA	-21.426	2.2e-16	-10.905	2.2e-16	-40.651	2.2e-16
EMD-ARIMA*VMD-ARIMA	-48.247	2.2e-16	-21.67	2.2e-16	-784.75	2.2e-16
EMD-ARIMA*ARIMA	-22.039	2.2e-16	-10.926	2.2e-16	-44.481	2.2e-16
EMD-ARIMA*BPNN	0.96219	0.3369	0.50678	0.6127	-0.23849	0.8117
VMD-ARIMA*ARIMA	63.274	2.2e-16	23.04	2.2e-16	169.32	2.2e-16
VMD-ARIMA*BPNN	47.55	2.2e-16	21.656	2.2e-16	778.01	2.2e-16
ARIMA*BPNN	21.283	2.2e-16	10.877	2.2e-16	41.463	2.2e-16

than the ARIMA model. The EMD-ARIMA model outperformed the VMD-ARIMA model. A comparison between the EMD-BPNN and the VMD-BPNN models, shown that the VMD- BPNN model has an edge over the EMD-BPNN based on the MAE, RMSE and MAPE. Regarding the values of MAPE, the order of the six models, in ascending order, is BPNN model (0.13861%), EMD-ARIMA model (0.14021%), VMD-ARIMA model (0.14368%), ARIMA (0.80577%), and EMD-BPNN model (55.94444%). The decomposition techniques turn to increase the predictability of the ARIMA model but fail to improve the forecasting ability of the BPNN model.

L. PAIRWISE COMPARISON OF SUGGESTED MODELS OF GOLD BASED ON DM TEST: TWO-SIDED

In the same manner, the suggested models of gold were subjected to a DM test to rate the predictability accuracy of the proposed models, as presented in Table 11. According to the DM test, BPNN has the best forecasting accuracy in predicting gold futures prices series. The VMD-ARIMA emerged as the second best model, followed by EMD-ARIMA in predicting gold futures prices series with DM values of 2.3704 and 3.5306, respectively. The performance ability of the various models is summarized in Table 9. It is recommended that in forecasting futures prices series of gold, the BPNN model should be considered.

V. CONCLUSION

In this study, we presented two decomposition techniques (EMD and VMD methods), combined with BPNN and ARIMA, to forecast the futures prices of three types of commodities: corn, crude oil, and gold - selected across the commodity market. The EMD and VMD were utilized to decompose the three commodities futures prices series into IMFs, residue and modes to predict commodity futures prices. To improve the forecasting ability and accuracy of BPNN and ARIMA, we compared the forecasting capability of the techniques using the three predicting performance rating criteria - MAE, RMSE, and MAPE. We also performed Diebold Mariano test to select the optimal model, since the MAE, RMSE and MAPE have some specific limitations. In addition, we examine the causal relationship amongst the three commodities futures prices series.

It emerged that, the combined models proposed outperformed the standard models, BPNN and ARIMA, in predicting futures prices series of corn and crude oil but failed in forecasting the gold futures prices series. It was also established that there are causal relationships amongst the three commodities futures prices series.

We draw the following conclusions from our findings: (1) the VMD-ARIMA outperforms the EMD-BPNN, EMD-ARIMA, VMD-BPNN, BPNN, and ARIMA models for corn future prices series, with regard to the three predicting performance test standards, MAE, RMSE, and MAPE. These findings suggest that the VMD-ARIMA model is the optimal model in terms of flexibility in capturing volatility in predicting the price of corn while the EMD-ARIMA is the best predicting model for crude oil, and the BPNN model is the robust method for predicting gold futures prices series; (2) the forecasting performance of combined models methods have more acceptable performance than the ARIMA model in every instance of this experiment; (3) the forecasting capability of VMD-BPNN model is more robust than the EMD-BPNN model, the EMD-ARIMA model, and the VMD-ARIMA model, suggesting that VMD method is more suitable for the prices data pre-treatment since it raises the forecasting precision and (4) using a combined model approach, policymakers, government, and businesses can take prudent decisions to minimize loss and maximize profit. It is recommended that researchers who predict commodity market prices should consider the decomposition approach since it improves the predictability of price fluctuations.

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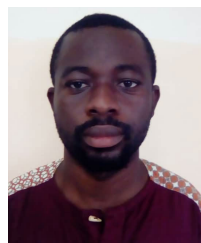
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