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Forecasting Price Direction and Spread Options in Oil Volatility

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ABSTRACT

The energy market aims to manage risks associated with prices and volatility of oil asset. It is a capital-intensive market, rippled with a range of chaotic, complex and dynamic interaction among its supply and demand derivatives. Models help users forecast such interactions, to provide investors with empirical evidence of price direction. Evolutionary modeling is an art, whose science seeks to analyze input data and yield an optimal, complete solution for which conventional methods yield a corresponding, non-cost effective solution. Its solutions are tractable, robust and low-cost with tolerance of ambiguity, uncertainty and noise as applied to its input. Our study aims to predict the oil market with data collected over the period.

Keywords - Energy, OPEC, price direction, volatility, FUPRE, stochastic, evolutionary models, unsupervised.

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1. INTRODUCTION

Asset market has become focal point for diversification in the finance world with the oil (energy) market playing a dominant, crucial role. The increased supply and heavy demand dependence on oil has brought about a number of complexities ranging from production, transportation and stringent regulation issue, all of which continue to plague its effective management (Laurenti and Fernandes, 2012). Market participants invest, knowing that such asset yields interesting diversification benefit, reward and positive investment returns to their financial portfolio (Ojugo, 2016) as oil now accounts for over 10% of the world's actively traded assets and largest consumed asset (Verleger, 1993). Thus, investors continue to seek effective means to trade in the future via its supply and demand parameters (Ojugo and Ofualagba, 2016) based on empirical results and analytic findings that helps to further dispose participants to the oil (energy) market. The recent plummet in price, seem like an indication to the end of the oil-era. However, studies show (Fig. 2) that the global demand of oil continues to rise despite that demands from Organization for Economic Co-operation and Development (OECD) nations has decreased. But, OPEC data shows that Oil's overall demand is increasing with demands from non-OECD nations like China (EIA Report, 2009); And, that a significant amount of oil is supplied from 'unstable' Middle East connotes that more price fluctuations is to be welcomed as normal. Thus, prediction of oil price direction is useful for investors and market participants (Ojugo, 2016).

Taking a position in spot market, is not the best way to react to new data as such decision is besieged by high transaction cost, storage and delivery costs, high premium among others inconveniences etc – especially if the investor is not interested in such asset; Rather hedging for another asset or speculating by simply investing in hope of arbitrage opportunity. Thus, futures market is more attractive because an investor can react to new data for the right reason (Silvapulle and Moosa, 1999). Many studies have reported inconsistency and discrepancies in the findings relating to spot- and futures-price. And whilst many of these studies agree on the importance of futures prices; only a few agree how important it is, as majority of the studies are based on analytic models. Moshiri and Foroutan (2005) examined the non-linear and chaotic feat in futures prices, comparing the ARMA/GARCH linear models against nonlinear ANN model. Result showed ANN is statistically more significant and outperformed both ARMA and GARCH as futures price is stochastic and nonlinear. Wang et al (2005) in their hybrid model, merged web-mining for rule extraction, ANN and ARIMA model and claims the nonlinear integration of these 3-models outperforms any single model.

Kulkarni and Haidar (2009) used ANN to predict price and volatility, claiming their model perform better. They observed two errors in Wang et al (2005): (a) the use of raw data input in ANN, and (b) training dataset used, is quite old for the period used. However, we note these error also in Kulkarni and Haidar (2009): (1) the controversial, unreliable nature of their rule-base system depends on a knowledgebase designed by expert (though, many experts' opinion(s) vary on the same task; Thus, theirs cannot be said to be more authentic and final), (2) their knowledgebase or its corresponding rules were not made available for further verification, and (3) a systemic errors in their design using feedforward net (which treats all data as new; but, we know that such new data become historic data after some iteration, and should not be used (as in their claim) as it cannot help the

network identify feats of interest. In broadening our data length coverage, we treat all data (previous and current) as input for in-sample forecast, even if the data exhibit temporal dependence. A major error in their design is that as network grows larger via adding more data, feedforward network are practically difficult to implement (Ojugo et al, 2013a,b). Our study presents a GANN model to predict price and volatilities using Gabillon model as model preprocessor.

2. MATERIALS AND METHODS

2.1 Motivation

Even with the many studies/tools to re-investigate prediction of oil futures price; we draw our statement of problem as thus:

1. Does plummet of 'expected-rise' in futures price imply that previous studies did poor forecast. We need to know why and how it happened.
2. Future price is a continuous 'inconclusive' task. Forecast only provides us with insights into expected values with continued enhancement of futures price via sample-period update and broadening of data coverage.
3. Price forecast is crucial; But, costly. Even so, obtaining the best possible forecast is of paramount importance and priority.
4. The chaotic, volatile nature of oil market makes accurate prediction imperative. Observing the spot prices alone is insufficient as unknown input can yield inconclusive results along with false-positive and true-negative error in classification activities (resolved in Section 3).
5. Dataset is rippled with ambiguities, impartial truth and noise – to be resolved via a robust search that effectively classifies data input and expected values (as in Section 3).
6. Most **unsupervised** models adopt hill-climbing method, which imposes speed constraint on NN and often trapped at local maxima. Hybridization resolves this. Also, model must be able to resolve statistical dependencies imposed on it by hybrid method and dataset (see Section 3).
7. To avoid overtraining, over-parameterization (inadequate or improper parameter selection) and over-fitting in the model, we use a larger dataset to help in its generalization as it seeks underlying probability in data feat(s) of interest as resolved in Section 3.

The proposed genetic algorithm trained neural network aims to predict futures price and volatility as it propagates data (observed/current) to seek feats of interest.

2.2 Gabillion Models

Gabillon (1991) model was extended Gibson and Schwartz (1990) model for futures price forecast. The model assumes futures price depends on: (a) spot price of Oil and (b) cost to carry the physical oil. Investor's attitude towards the spot price risk(s) and expected increase in spot price are irrelevant to the pricing of a futures contract on Oil. Spot price is given by Eq. 2 where μ(S) is mean (expected drift rate per unit in time) and σ(S) is standard deviation (volatility of the process), and dz is Wiener process given by:

$$dS = \mu(S)dt + \sigma(S)dz \qquad (1)$$

The futures price for short-term, independent of the stochastic process of the spot price with r as riskless interest rate, C_c as marginal carry cost, C_y as marginal convenience yield and C_p is marginal influence yield, as given by:

$$F(S, z) = Se^{(r+C_c-C_y+C_p)z} \qquad (2)$$

We include C_p shock for these reasons: (a) energy is about dominance. Nations seek to less dependent on others, for the more a nation depends on another – the more influence such nation she depends on, exerts her politics and policies over her, and (b) this creates new frontier for international politics with franchises made, nation policy interest aligned, treaties brokered; And thus, leads to off-channel sales via diversion tactics from non-OPEC nations, non-observance in limit placed by regulatory bodies like OPEC etc.

2.3 Artificial Neural Network

Our Jordan net is constructed by adding a context layer to (modify) a multilayered feedforward. This will help it retain data between iterations. On start of the algorithm, the context layer is initialized to zero so that output from first iteration is fed back as input into hidden layer (Perez and Marwala, 2011) – so that for the next time step, previous contents of the hidden layer are then passed unto **context** layer, which helps to yield a new input that is also resent back again as into hidden layer in another time-step (Regianni and Rientjes, 2005). Weights are recomputed in same manner for new connections fro/to its **context** layer from hidden layer. And, training aims at best fit data weights computed via Tansig function, which assumes an approximation influence of data points at its center. Thus, the function decreases with distance from its center.

Its Euclidean length (r_j) is distance between vector y = (y_1, . . . ,y_m) and center (w_{1j},...,w_{mj}) as:

$$r_j = \left\| y - Y^j \right\| = \left\{ \sum_{i=1}^{m} (y_i - w_{ij})^2 \right\}^{1/2} \quad (6)$$

The suitable transfer function is applied to r_j:

$$\emptyset(r_j) = \emptyset \left\| y - Y^j \right\| \quad (7)$$

Finally, output k receives weighted combination as:

$$y^k = w_o + \sum_{j=1}^{n} \left(c_j^k * \emptyset(r_j) \right) = w_o + \sum_{j=1}^{n} \left(c_j^k * \emptyset \left\| y - Y^j \right\| \right) \quad (8)$$

2.3 Genetic Algorithm (GA)

GA consists of a population propped for selection via evolution principles so that each potential solution is an individual for which optimal is found using four operators as below (Coello et al, 2004 and Reynolds, 1994). Its fitness function determines how close an agent is to optimal solution so that agents that are close to its fitness value are said to be fit. The operators include (Ojugo et al, 2013a,b): initialize, selection and fitness function, crossover (recombination) and mutation.

3. DATA SAMPLING AND COLLECTION

A critical feat in ANN is its dataset size and frequency. This affects its final result. For short-term forecast, high frequency data is preferred (i.e. daily) though when available, is costly. Thus, we use the less noisy weekly/monthly data. Another feat is data coverage (Kulkarni and Haidar, 2009). The more data point is used in ANN, the better its generalization. Some modelers discard older dataset as economic conditions change in time. Smith (1993), McNeils (2005) and Kulkarni and Haidar (2009) believe that training ANN with old irrelevant data alongside current conditions can result in poor model generalization. However, we believe that broadening our data coverage helps ANN avoid pitfalls of over-parameterization, overtraining and over-fitting. OPEC data is available: investexcel.net/opec-basket-histor-excel.htm.

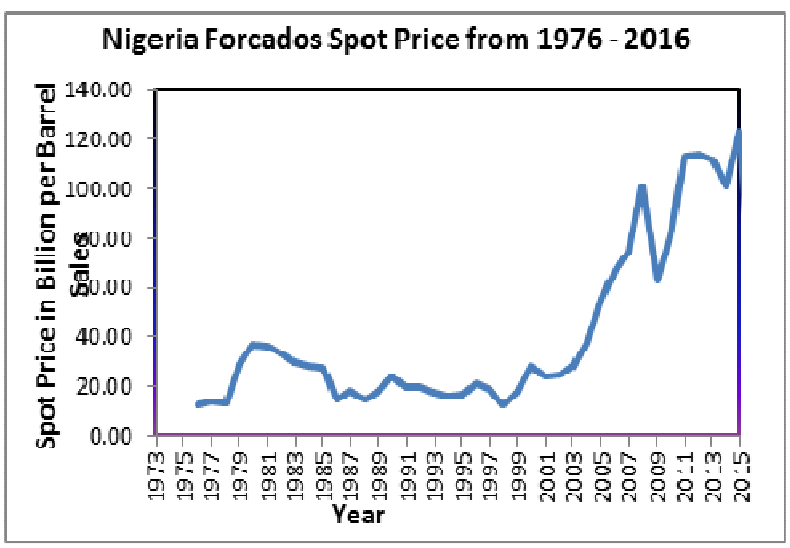

Fig 1: Nigerian Forcados Spot Price with Date

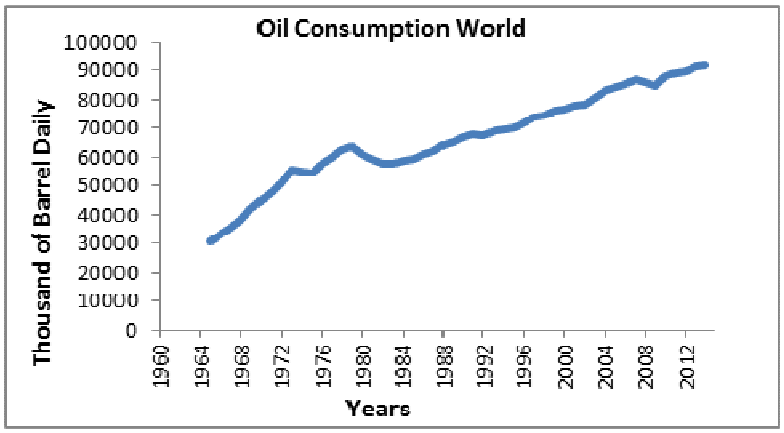

Fig 2: Worldwide Consumption of Oil

The study is limited to secondary data obtained from Energy Information Administration on monthly all countries spot price and consumption of crude oil from March 1976 – December 2015. The GANN model is used in the computation of the price direction and implied volatility used to determine the fluctuations in price direction; while some other trading strategies used in hedging commodities like oil are looked at.

3. 1 Rationale of the Model

1. Gabillon Model yields a good start point solution for our memetic (GANN) model. All data are treated as new in a feedforward net. Previous data do not help to identify data feats of interest (here, accurate price and volatility) even if such observed data exhibits temporal dependence.
2. The structural dependencies imposed by the data and on the hybrid model via adopted methods, is resolved via its capability to store earlier generated dataset from previous layer(s) unlike in feedforward nets that must be expanded and extended to represent such complex, dynamic patterns and scenario as this (Kuan, 1994; Ojugo et al, 2013).
3. As network becomes larger and more data are fed in, feedforward net makes it practical difficult to implement. We overcome this via our **Jordan** net's internal feedbacks that inputs back previous output into the hidden unit with a time delay so that output at t+1 becomes input at later t – making it better suited for such task.
4. Jordan is more powerful and computationally plausible. Its backpropagation-in-time algorithm uses output at t, as input alongside new input to compute the output at t+1 in response to market data changes (Mandic and Chambers, 2001) via Tansig activation function y^k. It sums all input, receives target value of input patterns, compute error data, weight correction updates in layers (c_j^k) and bias weights correction updates (c_o^k). Its error is sent back from output layer into input nodes via error backpropagation (to find weights that yields target output with selected accuracy) to correct its weights. Weight is modified by minimizing error between target and computed outputs, at the end of each forward pass. If the error is higher than selected value, process continues with a reverse pass; else, training stops. Weights are updated via mean square error until a minimal error is achieved (Ursem et al, 2002).

3.2 Experimental Model

Our model hinges on: (a) Gabillon model, (b) Jordan net, and (c) Genetic algorithm. Data pre-processing is a sensitive task as it often destroys the inbuilt structure in an original dataset (Azoff, 1994; Vanstone, 2005). Thus, as opposed to the use of a weak stationary process, we implement thus:

1. ANN's learning ability with advanced algorithms such as backpropagation with momentum help us resolve issues in using a weak stationary process as justified by Kulkarni and Haidar (2009).
2. The behaviour of the oil market is rippled with shock and fluctuations (volatility). It forms a focal point to forecast price direction. Parameter selection, dataset and modeling of oil market is critical and must reflect such behaviours.
3. As justified by Kulkani and Haidar (2009), replacing non-stationary, dynamic data with weak-stationary ones will lead to false-positives and true-negatives result, which will also mislead market participants and policymakers.
4. Influence of shock cannot be overemphasized. Though, it lingers over many steps, accuracy must not be trade-off for easy implementation and likely agreement of result.
5. Using non-stationary data makes easier ANN to estimate general characteristics and feats in dataset; rather, than actual relationship (Refenes, 1995). Thus, data looses originality, quality and inbuilt structures via such transformation advocated in Kulkarni and Haidar (2009) since forecasts retrieved overtime as result has the same nature and structure required as output for forecasting price direction and volatility.

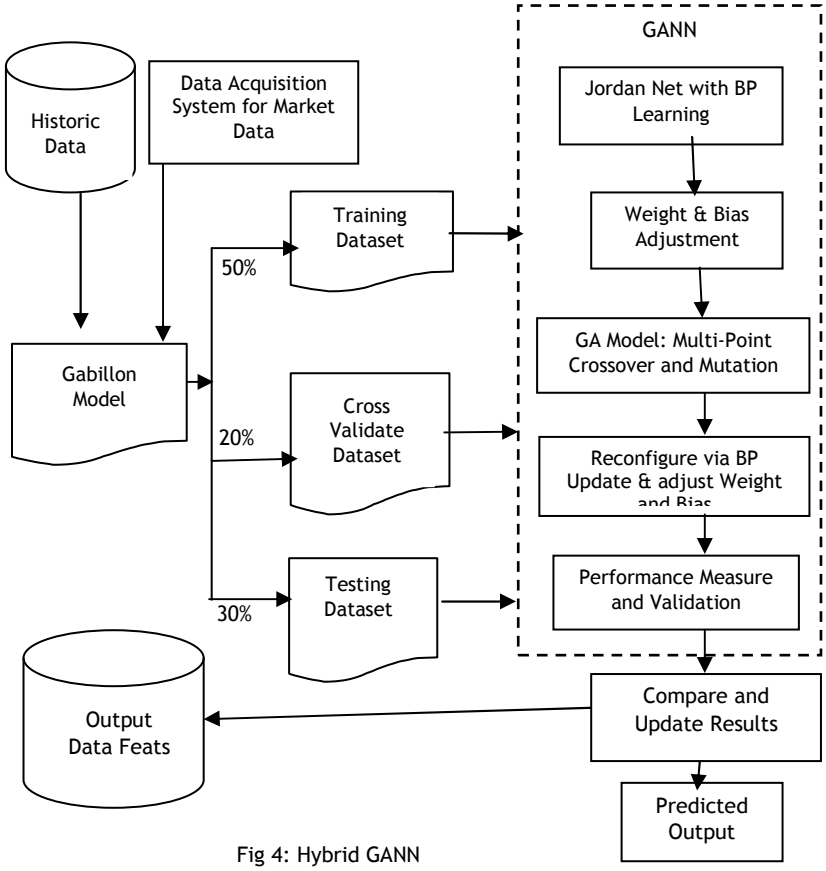

Fig 4: Hybrid GANN

The market as a model that allows data (historical, current and update samples) as input. Thus, participants react based on their dispositions, speculations, analysis etc to result in an output closing price, which is an aggregation of the activities. Imitating this, our model maps the adopted data to a desirable target so that its forecast is with a certain degree of accuracy and an acceptable degree of error (Refenes, 1995). We use ANN as nonparametric and nonlinear mapping-model (Azoff, 1994) with no prior assumptions – so that the sample updates used as data coverage is expanded to help model recall price direction for better forecast. And the dataset is harnessed to speak for itself (Azoff, 1994). Unlike Kulkarni and Haidar (2009), we adopt a recurrent Jordan net, which is best suited to estimate nonlinear, continuous function (oil prices direction), test if futures prices with newer data predicts price direction, and if data in futures price integrated with spot-price yields better forecast, as in fig 4.

3.3 Data Modeling and Parameter Selection

The proposed experimental model is employed as:

a. First, we use the Gabillion model as a preprocessor classifier to help forecast futures prices and volatilities of contracts in the oil market. This will in turn propagates the values of selected data as further input to the model as enhanced, defined variable classes that are partitioned into data-points.

b. Dataset is grouped into: training, retraining and testing, and used to initialize the GANN model. The Jordan net is an unsupervised, self-learning model whose optimization is achieved via GA's recombination and mutation. For our Jordan net, we use multilayered perceptron (feedforward) net with short-memory (i.e. time-lag network) with local recurrent connections, which requires a smaller network to learn temporal task. Irrespective of how large network and data grows, it is more plausible and computationally more powerful than other models through its momentum learning and backpropagation-in-time that trains the net so that output at t is used along with new data to compute output at t+1 in response to the phenomenon's dynamism and chaotic nature.

GA recombines and mutates the dataset so that model autonomously forecasts futures price. Model is initialized for data selection via the preprocessor Gabillon model. Knowledge of the task has direct impact on how model processes the data, determines how close a solution is, and how the algorithm is employed. Model stops as best individual has a fitness of 0 (Campolo et al, 1999; Dawson and Wilby 2001b). Our ANN uses BP-in-time and momentum learning, which uses error derivative propagated back to neurons to adjust its weight updates as thus (Ojugo et al, 2015a,b,c):

1. Set all weights to small random values.

2. Input to each node: x_i input from previous node, w_i is weight – so that sigmoid function computes thus:

$$Input\ \alpha = \in X_i W_i \quad (9)$$

$$Output\ Y = f(x) = \frac{1}{(1+e-x)} \quad (10)$$

3. Its errors, desired and actual output is sent back to nodes with updated weights via Eq. 10 (w_{ij} is weight from node i to j at t, ŋ is learning rate, oj is output of j; μj is error for node j).

   So:

$$W_{ij}(t+1) = W_{ij} + \eta \mu j oj \quad (11)$$

   Output node: $\mu j = koj(1-oj)(tj-oj) \quad (12)$

   Hidden nodes with μ_k as next nodal error term:

$$\mu j = koj(1-oj) \in \mu k.wjk \quad (13)$$

We then initialize GANN with data from Gabillon model. Data is selected from the pool via the tournament method (is easier and more efficient to code, and best suit for parallel architectures. Its selection is easily adjusted as it allots random numbers to data agents). Fitness function is computed to determine mating agent and corresponding solutions. These are made available as a new pool from single parent. We use a multipoint crossover to introduce chaos and volatility as in the market. Mutation helps the network to learn all non-linear, dynamic feats in dataset.

With agents in original pool from single parent, network uses Gaussian distribution to randomly generate data corresponding to crossover points. And as new parents contribute to pool, it yields new agents whose genetic makeup is a combination of both parents. Mutation is applied to yield agents that also undergo further mutation that re-allocates to them new random values. The number of mutation applied depends on how far GA progresses on the model (i.e. how fit the fittest agent is in the pool). This equals the fitness of the fittest individual divided by 2. New agents are selected to replace old ones of low fitness, and create new pool. Process continues until individual with a fitness value of 0 is found - indicating solution has been reached (Branke, 2001).

4. RESULT, DISCUSSION AND FINDINGS

4.1 Experimental Findings and Analysis

Recurrent net converges after a longer time; But, our hybrid speeds up ANN process so that model converge after 3minutes and 29seconds with 500 iterations. While, net keeps various numbers of previous steps in memory (context) layer, its result varies for each retraining time-step and is in tandem with the chaotic and dynamic conditions of the dataset and volatility. Though Jordan NN require more hidden neurons to converge due to context layer, our use of MLP with momentum – works in place of it. Choice of activation function, weight/bias, and learning rate are determined by the experiments. The model leads to fast convergence, and higher hit rate.

Fig. 5 show futures price direction monthly forecast for 2017. The spot price for each month is monthly average oil price (dollars per barrel) and its volatility is estimated from prices in previous year. For 2017, volatility varies between 1.9012 and 0.312; And for 2018, volatility varies between 0.16 and 0.3542 for 12-months (52 weeks) futures maturity. Thus, the oil price still go up due to demand; Rather, than plummet in the near future. However, energy is about dominance and a lot of international politics are displayed when energy is concerned due to vested interests. These result in various shocks ranging from convenience yield etc.

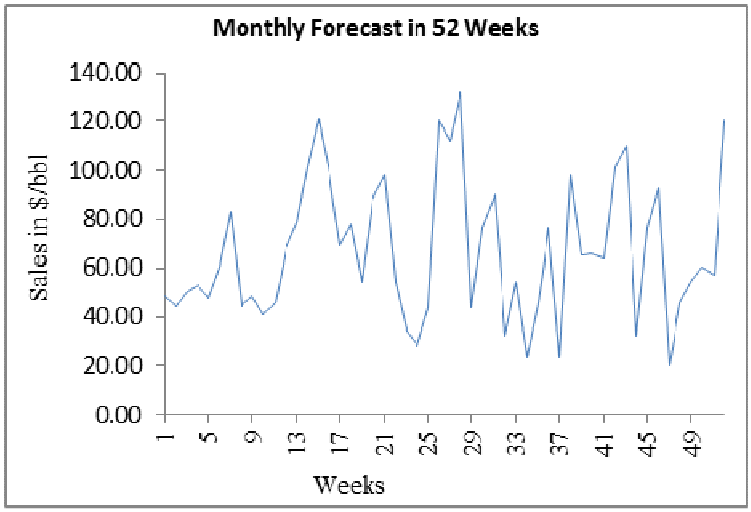

Fig. 5: Futures price direction and volatility

Also, studies of oil price direction emphasize the role of interest rates and convenience yield (adjusted spot-futures spread) to confirm that spot price normally exceed discounted futures. Though most studies do not explain why such 'backwardation' is normal, it is a result of hedging and speculations. We also noted it is far better to hold a physical asset than hold futures contracts as proposed by hedging. Also, convenience yield behaves nonlinearly; And, price response to convenience yield is also nonlinear. Thus, futures price are informative about future spot prices only when spot prices substantially exceed futures.

Producer hedging is observed as a way forward such that if spot-price of oil is $x/barrel at t and producer expect price to fluctuate between t and T (maturity time for hedge). If producer is more concerned about risk of prices falling below $y/barrel and prepared to accept maximum price of $z/barrel. Hedging allows participants to buy at $y/barrel **put** and sell at $z/barrel **call**. This limits backwardation (downside) and contango (upside) price risks to the range between $y/barrel and $z/barrel. If oil prices falls below $y/barrel at t, $z call option is worthless and the $y put option is exercised to grant the producer the right to sell its output at $y/barrel (no matter how low prices go). If prices rise over $z/barrel, the $y put option becomes worthless as $z call option is exercised and producer will sell at $z/barrel (no matter how high prices go).

But, if prices are between $y/barrel and $z/barrel, neither of the options is exercised so that the producer sells at the prevailing market price. This is known as a **collar**. The strike price of the option can be set at any level, but the put and call options must be equally far out-of-the money if the cost of the put and call is to be the same. If the costs of the options are the same, the strategy is known as a zero collar (Cherry, 2007; Dontwi, Dedu and Davis, 2010).

4.2 Model Performance

We evaluate the performance of the models via its computed coefficient of efficiency, mean square error, mean absolute error, mean relative error, and coefficient of efficiency. A model with minimum error is considered, best choice. Model validation should not be performed by single researcher or research group; But rather, a scientific dialogue – as the improper model application along with its ambiguous results often presented by modelers that impedes such dialogue. The aim of this hybrid thus, is to a great extent minimize and reduce the confusion in financial data time-series. We use the MLP model as a benchmark to measure model performance.

Table 1: Comparative Model Performance

	Training			
Model	COE (R)	MSE	MAE	MRE
GGANN	0.982	0.282	0.328	0.213
MLP	0.515	0.4309	0.665	0.8708
Cross-Validation				
Jordan	0.892	0.329	0.231	0.1901
MLP	0.512	0.686	0.712	1.109
Testing				
Jordan	0.966	0.296	0.219	0.1710
MLP	0.641	0.654	0.518	1.385

5. DISCUSSION OF FINDINGS

The following recommendations were made:

1. Nigeria is a mono-product, reactive nation. Her policy makers must devote great effort towards regular updates in price change for effective implementation as she seeks new funding alternative. She must open her investments that improve her local contents and human capital as the futures prices will fluctuate more due to volatility.
2. Energy is about dominance, and nations seek to less depend on assets that enslave them to others as possible.
3. Our analysts should always strategize to keep up with new innovations and paradigm shift from one source of energy to another. Thus, with a plummet or outright non-dependence, we have to be prepared for such outcomes.
4. Cutting edge innovation will always advance as vehicles for great change. Nigeria cannot be left out in this change.

Oil is vital for economic growth. The oil market is engulfed and endangered by speculations in the finance market, politics, extreme weather phenomena, among others – which accounts for its increased volatility. The price fluctuation effect extends its influence over a large number of goods and services with direct impact on economies. To reduce its negative impact, it is imperative to predict price direction(s) regularly. But, some fundamental parameters (e.g. oil supply, demand inventory, GDP, seasonal data, jumps and spikes etc) are not readily available on daily scale. These dynamic and chaotic events all adds to the complexity involved in the prediction of oil price and volatility (Kulkarni and Haidar, 2009).

Focus on models to predict price direction and volatility must continue – as futures price reacts faster to new data than spot price. The forecast allow investors to harness the benefits of the market such as low transaction cost, high liquidity, premium etc. Such infusion of new-market-related data help investors dispose themselves to either buy or sell in the market (Kulkarni and Haidar, 2009) with empirical results that beckon on investors to harness these merits without trading a physical asset; But, rather using only contracts or bonds (Ojugo, 2016). To judge the price implication of fitting structural models, or apply it as symbiotic informed decision – on other assets – all of which have different market structures and fundamentals, is time-consuming, non-cost effective and may not add no more value than just being an extrapolation from the spot price.

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