

# Investigating The Unexpected Price Plummet and Volatility Rise In Energy Market: A Comparative Study of Machine Learning Approaches

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## Abstract

Energy market aims to manage risks associated with prices and volatility of oil asset. It is a capital-intensive market, rippled with chaos and complex interactions among its demand-supply derivatives. Models help users to forecast such interactions and give insight with empirical evidence of price direction to investors. Our study sought to investigate the unexpected plummet in price of the energy market using evolutionary modeling – which seeks to analyze input data and yield an optimal, complete solution that are tractable, robust and low-cost with tolerance of ambiguity, uncertainty and noise. We adopt the Gabillon’s model to: (a) predict spots/futures prices, (b) investigate why previous predictions failed as to why price plummet, and (c) seek to critically evaluate values reached by both proposed deep learning model and the memetic algorithm by Ojugo and Allenor (2017).

*Keywords:* Energy market, deep neural network, machine learning, price volatility, futures price, oil, spot price.

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## 1. Introduction

Nigeria is arguably the most influential and most strategic country in Africa in view of its population, its vast hydrocarbon resources and her government’s commitment to anti-corruption and African Unity. Nigeria is heavily dependent on its oil sector which accounts for about 90 percent of export revenues and 41 percent of Gross Domestic Product (Kulkani and Haidar, 2009; Abosedra and Baghestani, 2004). Despite its relative abundance of mineral resources, the expansion of Nigeria’s oil sector has been stymied by its antiquated infrastructure and the frustrating slow movement of goods through Nigeria’s major ports. Nigeria’s rapid economic development has been largely to the deliberate policy of the government on technological capacity building via investment opportunities that exist in the oil and gas sector, human capital and institutional building. Technological growth in her oil and gas industry has been facilitated by a number of systematic and deliberate policies directed toward building of a network of institutions for the promotion of technological capacity (Ojugo and Allenor, 2017). Thus, capacity building and co-ordination have remained strategies since adopted by the Nigerian government for tackling the questions of technological backwardness (Azoff, 1994; Behmiri and Manso, 2013).

A reflection on the eve of the oil boom showed that the Nigerian agro-based economy was relatively diversified. There existed self-sufficiency in food production, with enough to feed the population and extra for export. The country had a strong export sector and budding industrial base. There were functioning laws, institutions, social and economic infrastructure as well as limitless job opportunities. Above all, security of life and property was adequate and foreign investors had confidence in the economy. This was the situation on ground before Nigeria’s first export of crude oil in February 1958. Since 1970s, the oil and gas industry has become the fundamental to the Nigerian economy, providing the bulk of revenue as well as the foreign exchange earnings for the country. The discovery of oil and gas opened up the industry, brought in foreign participations such as Mobil, Agip and Texaco/Chevron respectively to join the exploration efforts both in the onshore and offshore areas of Nigeria. This development was enhanced by the extension of the concessionary rights – which aimed to accelerate the pace of exploration and

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production of petroleum. The overall increased demand from the non-OECD nations, and consequent supplies from ‘unstable’ Middle East indicates that more price fluctuations and volatilities will be a welcomed normal (Bopp and Sitzer, 1987; Allenor and Ojugo, 2017). Thus, prediction of oil price direction is useful for investors and market participants.

### *1.1. The Energy Asset Market*

The asset market has become a focal point for diversification in the finance world with energy (oil) market playing a dominant role. Its increased demand-supply and the heavy dependence on oil, has advanced various complexities from production, transport, stringent regulation issue, marketing strategies (to mention a few). All these continues to plague the effective management of the market (Laurenti and Fernandes, 2012). Participants invest if an asset can yield benefits and positive returns to financial portfolio (Chan, 1992), and oil accounts for over 10% of the world’s actively traded assets to become the largest consumed asset (Vanstone, 2005; Verleger, 1993). With these, investors continue to seek effective means to trade (contract) in the future using empirical results in demand-supply derivatives (Gabillon, 1991) that further disposes them either positively or otherwise to the market. However, most investors are aware that the best way to react to new market data is not to take a position in the spot-price – since such decision is besieged by high transaction cost, storage and delivery costs, high premium among others inconveniences etc (French, 2005); Rather, they hedge for another asset, or speculate in hope of arbitrage opportunity. Thus, futures contracts are more attractive as an investor can react to new data for the right reason (Silvapulle and Mossa, 1999; Ojugo and Eboka, 2019; Ojugo and Eboka, 2020).

Previous studies have and continues to report inconsistencies and discrepancies relating to spot- and future-price. While, others studies advanced investing on future prices; only a fewer recognised how important future-price is – with many of such studies employing analytical models (IEA, 2009). Labonte (2004) used ANN to predict price and volatility. But, we note also error namely: (a) the controversial, unreliable nature of their rule-base system depends on a knowledgebase designed by expert (many experts’ opinion vary on the same task) and thus, cannot be said to be more authentic, (b) their knowledgebase (and rules) were not made available for further validation, and (c) systemic error in their feedforward net design (treats all data as new). We know that 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. Moshiri and Forotana (2005) examine chaotic feats in futures-prices, comparing ARMA/GARCH against ANN. They showed ANN is statistically significant and outperformed ARMA/GARCH as futures-price is stochastic and nonlinear.

Ojugo and Allenor (2017) explored a memetic (genetic algorithm trained neural network) algorithm cum model extending the Gabillon’s work. Their study noted that the energy market aims to manage risks associated with prices and volatility of oil asset. As a capital-intensive market, rippled with chaotic, complex and dynamic interaction among its demand-supply derivatives – investors sought to stay ahead of the tides with reliable data that steers their decisions in the right direction. They employed memetic algorithm to forecast the interactions of the various underlying parameters and provide investors with empirical evidence of the future contracts direction of oil price.

### *1.2. Motivation / Statement of Problem*

The problem characteristics is geared towards machine learning frameworks that models various feats as input parameters with an outcomes to predict futures-price and volatility rate to help investors with decision pointers for their financial portfolio. Thus, to re-investigate prediction of oil futures price – our statement of problem is (Ojugo and Allenor, 2017; Smith, 1993):

1. Does plummeting in the ‘expected’ futures-price imply that previous forecast were poor? And what implications does Ojugo and Allenor (2017) work of extending Gabillon (1991) hold therein as we seek to investigate what happened, why it happened and how it happened?
2. What minor shock (external and internal influences) spiked the plummet in the futures ‘expected’ price?
3. The chaotic and volatile nature of the energy-market makes accurate prediction imperative; But, just observing the spot-prices alone is insufficient as unknown input not present from the outset can yield inconclusive results along with too many false-positives and true-negatives error in the regression cum classification activities. Thus,

what pre-processing of the available dataset, what sample-period updates and broadening of data coverage will make for accurate predictions?

4. Many dataset(s) are riddled with ambiguities, impartial truth, incompleteness and noise. All of these must be resolved via a robust search that effectively classifies data input and expected values. These may also lead to over-parameterization and over-training of datasets and classification algorithms cum models.
5. To avoid overtraining, over-parameterization (inadequate/improper parameter selection) and over-fitting of the model, we use a larger dataset to help in its generalization as it seeks underlying probability in data feat(s) of interest. Earlier models adopt hill-climbing with speed constraints that often gets them trapped at local maxima. The adoption of deep learning is to resolve statistical dependencies imposed by both the adopted method as well as by the dataset employed during encoding and pre-processing cum preparation.

In extending Ojugo and Allenor (2017) whose result trends were acceptable for a period and observed to be faulty for some other predictions. Thus, this new investigation using various models to further compare previous predictions and other features employed. Also, to overcome many of these shortfalls inherent in the adoption of chaotic energy dataset, deep learning have been successfully adapted to handling such chaotic, dynamic and complex classification via a filtering techniques that seeks to de-noise dataset via trend normalization employed to enhance adequate classification.

## 2. Materials And Methods

### 2.1. Gabillon's Model

The focus is an extension of Ojugo and Allenor (2017) that sought to extend Gabillon (1991) – which also extended Gibson and Schwartz model for futures price. The model assumes futures price depends on: (a) spot-price, and (b) cost to carry the physical oil. Investor's attitude towards the spot-price risk(s) and expected increase in spot prices, are irrelevant to the pricing of a futures contract. Spot price is given by Eq. 2 – where  $\mu(S)$  is mean (expected drift rate per unit in time),  $\sigma(S)$  is standard deviation (volatility of the process), and  $dz$  is Wiener process as given by Eq. 1:

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

Futures price for short-term, independent of 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, yields Eq. 2:

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

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.

### 2.2. Data Sampling

A critical feat in modelling is dataset size and frequency. These affects/effects on the final result. For short-term forecast, high frequency data is preferred (i.e. daily); But, when available, is costly. Thus, we use the less noisy weekly/monthly data. Another feat is data coverage (Labonte, 2004) – for more data point used implies better generalization. Some modellers discard older data due to change in economic conditions (McNeils, 2005; Ojugo et al, 2012; Yoro and Ojugo, 2019s) – as they believe that training models with such irrelevant, old data along with current conditions may result in poor generalization. We posit that broadening our data coverage helps our model regression to avoid overtraining, over-parameterization and over-fitting. OPEC data is available: <http://www.investexcel.net/opec-basket-histor-excel.htm>.

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 net are practically difficult to implement (Yoro and Ojugo, 2019b; Schmidhuber, 2015) as an extension of Ojugo and Allenor (2017), we seek to investigate why the plummet in price direction in such a short while, what parameters in the model volatilities necessitated the nose-dive in the oil price still using Gabillon model as model pre-processor.

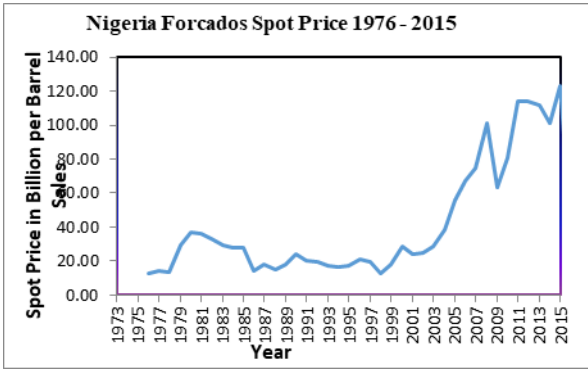


Fig. 1a. Nigeria’s Forcados Spot Price from 1973 – 2015

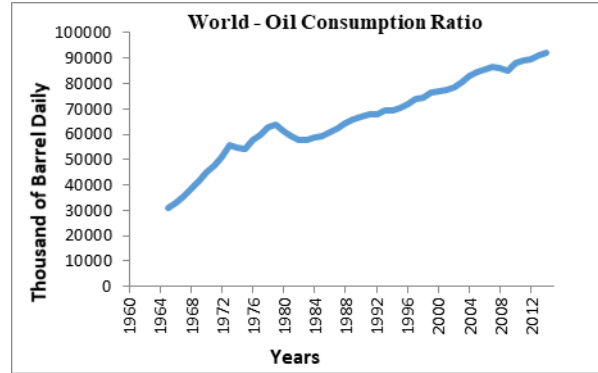


Fig. 1b. Worldwide Consumption of Oil

### 2.3. Deep Learning Neural Network

Deep neural network seeks to learn useful feats by constructing a multi-layer net from vast amount of training data. It has improved forecast accuracy with deep architectures of input, output and multiple hidden layers. Each hidden layer conducts a non-linear transformation from a previous layer to the next (Bengio et al, 2013; Hinton et al, 2012). Deep neural network as proposed by (Glorot and Bengio, 2010) is trained using two (2) phases namely: (a) pre-trained, and (b) fine-tuned processes.

Auto-Encoder is a type of unsupervised three-layered network whose output target is input data shown in Fig 1, with both an encoder and decoder network. The encoder transforms input from high-dimension into a low-dimension space with its encoding function  $f_{\text{encoder}}$  – where  $x^m$  is a data point and  $h^m$  is the encoding vector obtained from  $x^m$  as in Eq. 3 (Ojugo and Eboka, 2018; Ma et al, 2016). The decoder remodels input from previous steps, as a reconstruction function  $f_{\text{decoder}}$  – where  $x^m$  is decoding vector obtained from  $h^m$  in Eq. 4. Ma et al (2016) in (Erhan et al, 2010) details specific algorithms for encoding/decoding respectively, and on sparse, auto-encoders, de-noise of auto-encoders.

$$h^m = f_{\text{encoder}}(X^m) \quad (3)$$

$$X^m = f_{\text{decoder}}(h^m) \quad (4)$$

Pre-Training: N auto-encoders can be stacked to pre-train an N-hidden-layer DNN. When given an input, the input layer and the first hidden layer are treated as the encoder net of the first auto-encoder. Next, the first auto-encoder is trained by minimizing its reconstruction error. The trained parameter(s) of the encoder is then used to initialize the first hidden layer. Then, the first and second hidden layers of the DNN are regarded as encoder net of the second auto-encoder. Accordingly, the second hidden layer is initialized by the second trained auto-encoder. This process proceeds until the Nth auto-encoder is trained to initialize the final hidden layer. Thus, all hidden layers of the DNN are stacked in an auto-encoder in each training N times, and are regarded as pre-trained. This pre-training process is proven to be significantly better than random initialization of the DNN and conducive to achieving generalization in classification (Ojugo and Otake, 2018; Glorot et al, 2010).

Fine-Tuning is a supervised process that improves a DNN performance. The net is retrained with training data labelled, and errors calculated by difference between real and predicted values via back-propagated stochastic gradient descent (SGD). SGD randomly selects data samples, and iteratively updates the gradient direction with weight parameters. Best gradient direction is obtained with a minimum loss function. SGD’s merit is that it converges faster than traditional gradient descent methods, and it does not consider the entire dataset. This makes it suitable for complex neural networks (Erhan et al, 2010) and described in Eq. 5 below:

$$E = \frac{1}{2} \sum_{j=1}^M (y_i - t_i)^2 \quad (5)$$

$E$  is loss function,  $y$  is real label and  $t$  is the net output. Gradient of weight  $w$  is obtained as derivative of error equation – so that with the gradient of the weight  $w_{ij}$ , the updated SGD equation is defined by Eq. 6:

$$W_{ij}^{new} = W_{ij}^{old} - \eta \cdot (y_j - t_j) \cdot y_j \cdot (1 - y_i) \cdot h_i \quad (6)$$

$\eta$  is the step-size and it is greater than 0,  $h$  is number of hidden layers in DNN. This process is optimized and tuned by the weights and threshold based on the correctly labelled data. Thus, DNN can learn important knowledge for its final output and direct the parameters of entire network to perform correct classifications.

#### 2.4. Experimental Comparative Models

##### 2.4.1. Deep Neural Network Framework and Algorithm

Several model perform well given the benefits of their algorithms. They also can perform poorly when facing the complex and camouflaged data such as volatilities etc. Thus, the proposed approach is employed to solve the challenges above by: (a) training dataset divides training process and calculate center points from each training point, (b) each training data is trained by a corresponding DNN scaled the same as number of clusters so that each DNN learns all the various characteristics from each subset, (c) testing data subsets are divided into test datasets, which uses the previous cluster centers in its first step, and these subsets are applied to detect outlier by pre-trained DNNs, and (d) output of every DNN is aggregated for the final result of the spot and future price data outliers (Ojugo and Otakore, 2018). The proposed model-based solution is divided into 3-steps (Perez and Marwala, 2011; Erhan et al, 2010):

1. **Step 1:** Data is divided into training and testing. Training data is clustered. Centers from clustering process are stored to serve as initialization cluster center for generating testing dataset clusters. Because data feats indicate similar attributes of each type in raw dataset, points in the training dataset with similar feats are aligned into groups and regarded as same subset. To improve the DNN-model, its performance, different cluster numbers and values of sigma are considered. Number of clusters range from 2 to 6, and sigma from 0.1 to 1.0. Samples are assigned to one cluster by similarity. The minimum distance from a data point to each cluster center is measured. Each point is assigned to a cluster. Training subsets generated by clusters are given as input to DNNs. In order to train different subsets, the number of DNNs is equal to the number of data subsets. The DNN architecture consists of five layers: two hidden, one input, one softmax and one output layer(s) respectively. Two hidden layers learn feats from each training subset, and the top layer is a five-dimensional output vector. Each training subset generated from the  $k$ th cluster center is regarded as input data to feed into  $k$ th DNN respectively. Trained sub-DNN models are marked sub-DNN 1 to  $k$ .
2. **Step 2:** Testing dataset (subset of raw dataset) is used to generate  $k$ -datasets. The previous cluster center obtained from cluster in Step 1, are initialization cluster centers of the cluster algorithm in this step. The test sub-dataset are denoted as Test 1 through Test  $k$ .
3. **Step 3:**  $k$ -test datasets are fed into  $k$ -sub-DNNs, used to complete  $k$ -training in Step 1. Each output of sub-DNN is used to analyse positive detection rates, and confusion matrix is used to analyse performance of generated rules.

Our proposed DNN model classifies data, its weights and thresholds via back-propagation learning. Input vectors map low-dimensional space with DAEs and SAE [31, 34] to discover patterns in market datasets. Algorithm is thus:

**Input:** dataset, cluster number, number of hidden-layer nodes HLN, number of hidden layers HL.

**Output:** Final prediction results

*/\*Note the symbols of “/\_” and “\_/” represent comments in this algorithm.\*/\**

1. Divide raw dataset into two components: training and a testing dataset. */\*get the largest matrix eigenvectors and training data subsets\*/*
2. Obtain cluster center and cluster results. Here, the clustering results are regarded as training data subsets. */\*Train each DNN with each training data subset\*/*
3. Learning rate, de-noising and sparsity parameters are set and the weight and bias are randomly initialized.
4. HLN is set 40-nodes for first and 20-nodes for second hidden layer.

5. Compute sparsity cost function
6. Parameter weights and bias are updated
7. Train  $k$  sub-DNNs corresponding to the training data subsets.
8. Fine-tune the sub-DNNs by using backpropagation to train them.
9. Final structure of trained sub-DNNs is obtained and labelled with each training data subset.
10. Divide test dataset into subsets with SC. Cluster center parameters from the training data clusters are used.
11. Test dataset is used on each sub-DNNs, based on corresponding cluster center between the testing and training data subsets.  
/\*aggregate each prediction result\*/
12. Results are generated by each sub-DNN, are integrated and the final outputs are obtained.
13. **return** classification result = final output

2.4.2. *Memetic Algorithm (Genetic Algorithm Trained Neural Network)*

First, our Jordan net is constructed by adding a context layer to (modify) multi-layered feedforward network – to help it retain data between iterations. The context layer is first initialized to zero so that output from first iteration is fed-back as input into the hidden layer (Coello et al, 2004; Regianni and Rientjes, 2005) – so that for the next time step, previous contents of hidden layer are passed unto the *context* layer, yielding a new input that is also fed-back again as into hidden layer in another time-step (Ojugo and Yoro, 2013; Ojugo et al, 2013). Its weights are recomputed in same manner for new connections to/from the *context* layer from the hidden layer. Training aims at best fit weights computed via Tansig function and assumes an approximation influence of data at its center. As function decreases with distance from its center, its Euclidean length ( $r_j$ ) is distance between vector  $y = (y_1, \dots, y_m)$  and center  $(w_{1j}, \dots, w_{mj})$  given by Eq. 7 with a suitable transfer function applied to  $r_j$  to yield Eq. 8. The final output  $k$  receives the weighted combination as in Eq. 9 (Ojugo et al, 2015a; 2015b; Refenes, 1995; Heppner and Grenander, 1990):

$$r_j = ||y - Y^j|| = \left\{ \sum_{i=1}^m (y_i - w_{ij})^2 \right\}^{1/2} \quad (7)$$

$$\phi(r_j) = \phi ||y - Y^j|| \quad (8)$$

$$y^k = w_o + \sum_{j=1}^n (c_j^k * \phi(r_j)) = w_o + \sum_{j=1}^n (c_j^k * \phi ||y - Y^j ||) \quad (9)$$

Secondly, we use cultural GA, which consists of a population propped for selection via evolution principles so that each potential solution is an individual for which its optimal is found using four operators as below (Reynolds, 1994; Ojugo and Okobah, 2018; Cherry, 2007) – with fitness function that determines how close an agent is to optimal solution so that agents that are close to its fitness value are said to be fit. GA operators are (Ojugo et al, 2015a; 2015b): initialize, selection and fitness function, crossover (recombination) and mutation. For more details of the architecture and others, see [3] and other references can be made to (Ojugo and Eboka, 2019; 2020).

3. Findings and Discussion(s)

3.1. Evaluation of Models

We seek misclassification and improvement rates as summarized in Tables 1 via Eq. 10 and 11 respectively

Table 1: Misclassification Rate and Improvement Percentage for Each model

Model	Classification Errors		Improvement Percentages	
	Training Data	Testing Data	Training Data	Testing Data
Rule-Based GA	52.5%	23.2%	2.11%	3.6%
Neural Network (MLP)	48.4%	4.7%	2.32%	4.02%
Memetic (GANN)	19.6%	1.02%	0.09%	0.12%
DNN	1.23%	0.92%	0.09%	0.12%

$$Misclassification Rate = \frac{No. of Incorrectly Classified Rules}{No. of Sample set} \quad (10)$$

$$\text{Improvement Percentage} = \frac{MR(A) - MR(B)}{MR(A)} \times 100 \quad (11)$$

Table 1 shows misclassification rate with GA, NN and GANN yielding 23.2%, 4.7% and 1.02% (for test dataset) respectively; while the proposed DNN model has a classification error of 0.92%. Consequently, they all promise an improvement rate of 3.6%, 4.02% and 0.12% respectively for the GA, NN and memetic GANN; while the proposed DNN promises an improvement rate same as the hybrid memetic GANN model.

### 3.2. Classification Accuracy

With benchmark models (GA, NN and GANN), we compare how well our proposed DNN performs (see figs 2, 3 and 4). DNN outperformed all other models. The trade-off with GANN is in the modeller’s ability to resolve conflicts with data encoding, parameter selection and conflicts of statistical dependencies imposed by the hybrid. Though, contributed to its speed limitation – it is a merit for its flexibility, adaptation and robustness.

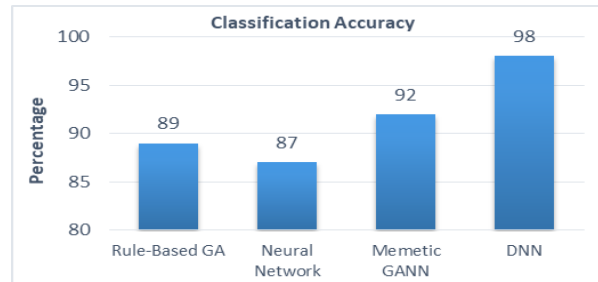


Fig 2. Classification Accuracy of the benchmark models against the DNN

### 3.3. Mean Processing Time

GANN is found to outperform our proposed model. This can be attributed to: (a) GANN first uses GA as pre-processor to train neural network, (b) though hybrids have structural dependencies on heuristics used and conflicts in data encoding to resolve, DNN can be slow due to the amount of hidden layers embedded in such model.

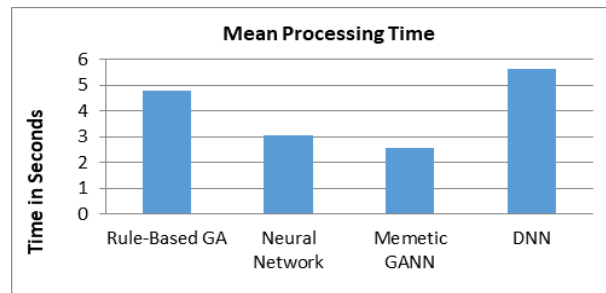


Fig 3. Classification Accuracy of the benchmark models against the DNN

### 3.4. Convergence Speed

GANN outperformed others as convergence time is proportional to mean processing time. Overall, DNN outperformed all other models and was been found to trade-off speed for accuracy due to amount of hidden layers.

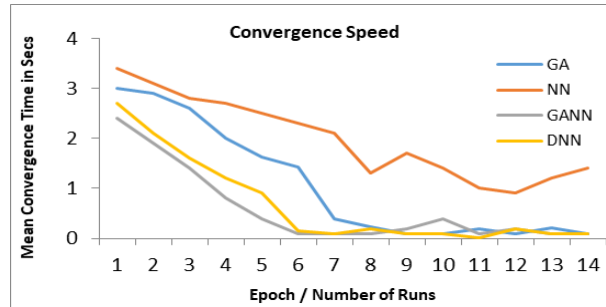


Fig 4. Classification Accuracy of the benchmark models against the DNN

3.5. Experimental Results of Proposed Model

Fig. 5 show futures-price direction monthly forecast for 2019. Spot-price is the monthly average oil price with volatility is estimated from prices in previous year. For 2017, oil price volatility varies between 1.9012 and 0.312; For 2018, volatility varies between 0.16 and 0.3542; while for 2019 – volatility varies between 0.412 to 2.092 for a 12-months period (52 weeks) futures maturity. Thus, the oil price still go up due to demand; Rather, than plummet in the near future. The results holds same for [3]. This may be a result of: (a) change in condition due to model training via older dataset, and (b) energy is about dominance – and, politics plays a crucial role due to concerns, policies and interests. These, in time results in various shocks ranging from convenience yield, internal influences etc (Coppola, 2007; Dontwi et al, 2010).

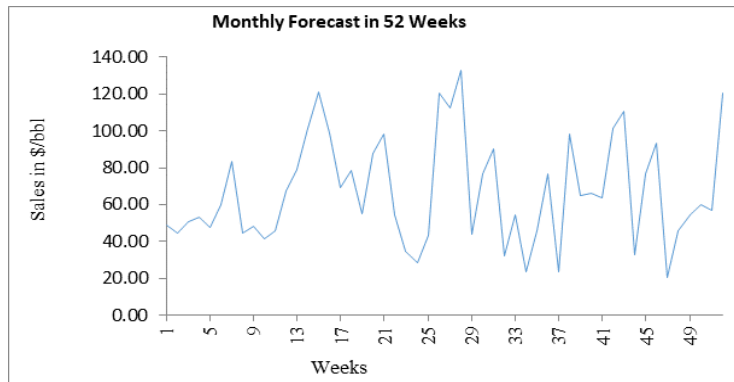


Fig. 5: Futures price direction and volatility

Oil price direction emphasizes the role of interest rates and convenience yield (adjusted spot-futures spread) to confirm that spot price normally exceed discounted futures-price. We explained earlier why such ‘backwardation’ is a welcomed normal; it can result to more hedging and speculations. We also noted it is far better to hold a physical asset than hold futures-contracts as posited by hedging. The convenience yield behaves non-linearly; And, price response to it behaves same. Thus, futures-price are informative insights about future-spot prices only – except when spot prices substantially exceed futures-price (Rouah and Vainberg, 2007; Sharma, 1998; Ursem et al, 2002).

Producer hedging is observed as a way forward, such that with spot-price is \$x/barrel at *t* – producers expect the price to fluctuate between *t* and *T* (maturity time for hedge). If a producer is more concerned about the risk of prices falling below \$y/barrel – he must prepare 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 and contango 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 and



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 costs of the options are the same, the strategy is known as a zero-collar (Ojugo and Allenor, 2017).

#### 4. Summary, Recommendation and Conclusions

The proposed DNN model has a total of 56-rules were generated. Top rules were found to have fitness range [0.8, 0.865] and are estimated 80% good to be used in classification of market clustering dataset. This implies that achieving a set of good rules – is much better than single optimum rule, which in turn is better for such clustering dataset. For comparative benchmark models (GA, NN, GANN), rule generator used population of 400,  $w_1 = 0.2$ ,  $w_2 = 0.8$ , 5000 epoch-evolutions and 0.05 probability of a solution to be mutated respectively. Future price and price volatility is a continuous, ‘inconclusive’ and herculean task with always-changing and chaotic dynamism due to the complex nature of the data inherent with the energy market. A forecast only provides us with insights into expected values with continued enhancement of futures price via sample-period update and broadening of data coverage. With future- and spot-price forecast as very crucial – even though, quite expensive and costly. Obtaining the best possible forecast is of paramount importance to many researches to aid investors with on the spot investment portfolios, power play and prowess as well as financial decisions.

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