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A Deep Learning Ensemble to Predict Energy Price Direction and Volatility on the Asset Financial Market

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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 that is rippled with chaos and complex interactions among its demand-supply derivatives. Models help users forecast such interactions, to provide investors with empirical evidence of price direction. Our study sought to investigate the reasons for 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 Allenotor (2017).

1. INTRODUCTION

Nigeria is arguably the most influential country in Africa in view of its population, its vast hydrocarbon resources and her government's commitment to African Unity. Nigeria is heavily dependent on its oil sector, which accounts for about 90% of her revenues and 41% of her Gross Domestic Product (Acemoglu et al., 2006; Ojugo & Yoro, 2020; Shahane et al., 2019). Despite the abundance, her energy sector has been stymied by antiquated infrastructure and slowed movement of goods via her ports. Technological development in her energy sector is facilitated by a number of systemic policies directed at a growing network of institutions to promote the need technological capacity. Thus, institutional capacity building and co-ordination have remained part of the strategies adopted by Nigerian government for tackling the questions of technological backwardness (Ahmad et al., 2016; Akin et al., 2010; Brunton et al., 2020).

Prior to the oil boom – Nigeria was an agro-based economy and relatively, quite a diversified nation. Her citizens were self-sufficient in food production – alongside enough to facilitate export (Alderson, 1937). She had quite a robust economy with functioning laws, institutions, socio-economic infrastructure with limitless job opportunities. This situation changed with the discovery of crude oil in February 1958. However, the 1970s birthed a new Nigeria – with a bulk of her revenue as well as the foreign exchange earnings accrued from the energy sector. This, saw an influx of foreign investors like Mobil, Agip and Texaco/Chevron vis-à-vis enhanced

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concessionary rights that aimed to accelerate the exploration and production of petroleum. The overall, undue increased demand from the non-OECD nations, and the unstable Middle East drove prices up. Thus, globally – price fluctuations and volatilities became a welcomed normal (Al-Turjman et al., 2019; Armstrong & Vickers, 2020). Thus, prediction of oil price direction is useful for investors and market participants. But, the increased demand-supply and the heavy dependence of many nations on oil, continues to advance several complexities ranging from production to sales (Dhanya & Nagesh Kumar, 2011; Obasi, Nwele et al., 2020).

With oil accounting for over 10% of actively traded assets, investors continue to seek effective means to trade (contract) in the future using empirical results in demand-supply derivatives (Duraisamy et al., 2019) 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; 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 (Ojugo & Yoro, 2020).

2. MATERIALS AND METHODS

2.1 Review of Related Literatures

Previous studies have and continues to report inconsistencies and discrepancies relating to spot- and future-price. While, many others advance on investing on future prices/contracts; only a fewer advance how important future-pricing is – with many of such studies using analytical models (Ampatzidis et al., 2020; Belanche & González, 2011; Laavanya & Vijayaraghavan, 2019).

Ojugo and Allenotor (2017) explored a memetic (genetic algorithm trained neural network) algorithm to extend Gabillon's model. 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 (Ojugo & Allenotor, 2017).

Okologume and Rotimi (2022) investigated the chaotic feats in futures-prices, comparing the ARMA and GARCH linear models against the nonlinear ANN. They showed that ANN is statistically more significant and outperformed ARMA and GARCH as futures-price is stochastic and nonlinear (Okologume & Rotimi, 2022).

Psaros et al., (2022) in extending the works of Kulkarni and Haidar (2009) used a deep learning model to predict price direction and volatility. They observed errors in Kalkani and Haidar (2009) to include: (a) the use of raw unprocessed data in reinforcement ANN model, which is often rippled with noise, ambiguities and partial truth, and (b) training dataset used is quite old, (c) 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, (d) their knowledgebase (and rules) were not made available for further validation, and (e) systemic error in their feedforward net design (treats all data as new). We observe and 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.

2.2 Study Motivation(s)

A major challenge inherent in machine learning approach prediction is the selection of the various underlying feats of interest as input parameters with an outcomes to predict futures-price and volatility rate to help investors with decision pointers for their financial portfolio (Ojugo & Allenotor, 2017; Ojugo & Otakore, 2020). Thus, to re-investigate prediction of oil futures price – our statement of problem is thus:

1. Does plummeting of the 'expected-rise' in futures-price imply poor and what implications does it hold? We seek to investigate what happened, why it happened and how it happened. What minor external/internal shocks influenced/spiked the plummet in the futures 'expected' price?
2. 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?
3. Many dataset(s) are rippled with partial truth, ambiguities, 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.
4. To avoid overtrain, over-parameterization (inadequate parameter selection) and model over-fitting, 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.

The study investigates: (a) the predicted trends of the benchmark Ojugo and Allenotor model as a comparative result of time convergence and accuracy, and (b) employ a deep learning model as means to help overcome the shortfalls inherent in the adoption of chaotic energy dataset. Deep learning models have proven to quite successfully, be 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.

2.3 Data Sampling

A critical feat in modelling is dataset size and frequency. These affects/effects on the final result. For short-term forecast, it is better to use high frequency data (i.e. daily); But, when available, it is quite costly to use. Thus, we use the less noisy weekly/monthly data. Another feat is data coverage for more data point used implies better generalization. Some modellers discard older data for change in economic states and conditions; This is because they believe that training models with such irrelevant, old data alongside current conditions can result in poor model generalization. OPEC data is available at: https://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. Thus, we seek to investigate why the plummet in price direction in such a short while, what parameters in the model volatilities necessitated the plummeting trend direction in the oil price.

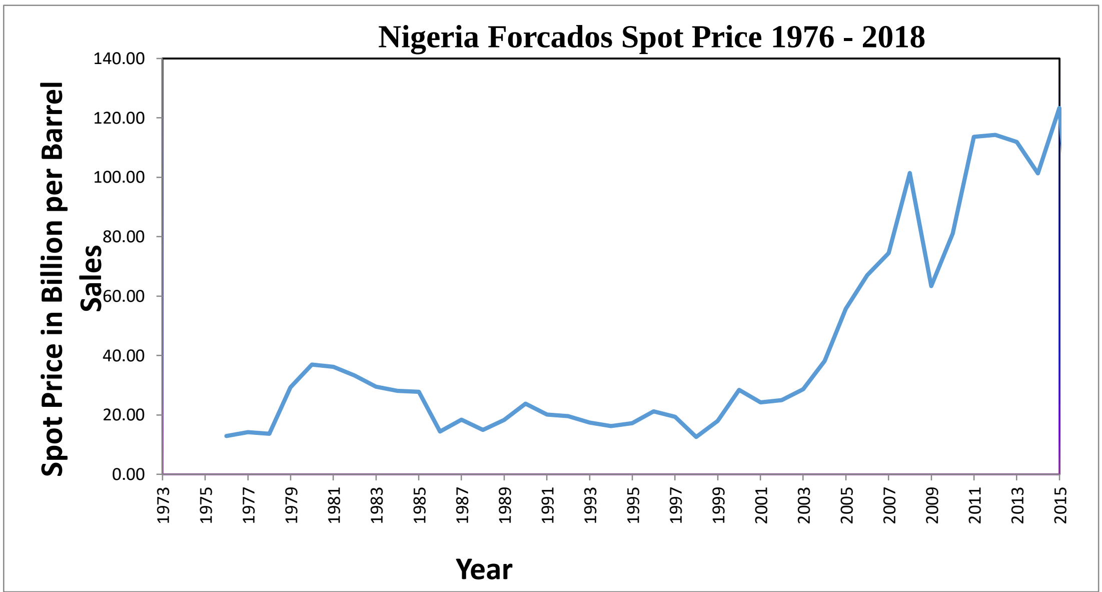


Figure 2: Base map of the study area

2.4. The Benchmark Gabillon Model

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 μ(S) is mean (expected drift rate per unit in time), σ(S) is standard deviation (volatility of the process), and dz is Wiener process as given by Eq. 1:

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

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:

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

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.

2.5. The Experimental Deep Learning

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. A deep neural network is trained using two phases: (a) pre-trained, and (b) fine-tuned processes (Ju et al., 2020; Jung et al., 2021). Several model perform well given the benefits of their algorithms (Nosratabadi et al., 2020; Verma et al., 2020). They also can perform poorly when facing the complex and camouflaged data such as volatilities etc (Camargo & Young, 2019; De' et al., 2020; Ojugo & Nwankwo, 2021c).

Thus, the proposed approach is used to solve the challenges above by: (a) training dataset divides training process and calculate center points from each training point (Ojugo et al., 2021; Ojugo & Eboka, 2021; Ojugo & Obruche, 2021; Ojugo & Oyemade, 2021), (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 (Allenotor et al., 2015; Allenotor & Ojugo, 2017).

Our proposed model-based solution is divided into 3-steps (Ojugo & Nwankwo, 2021a, 2021b, 2021d):

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**: The *k*-test data subsets are fed into k sub-DNNs, which were completed by the k training data subsets in Step 1. The output of each sub-DNN is integrated as the final output and employed to analyse positive detection rates. Then, confusion matrix is used to analyse mining performance of generated rules.

Our proposed DNN model classifies data, its weights and thresholds via back-propagation learning. The input vectors map low-dimensional space with DAEs and SAE (Ojugo & Ekurume, 2021a, 2021b; Ojugo & Otakore, 2021; Ojugo & Yoro, 2021) to discover patterns in the market data. The algorithm is detailed as in the listing 1 below:

Algorithm 1: EnDeLClusE Algorithm

Input: Dataset, cluster number, number of hidden-layer nodes HLN, number of hidden layers HL
Output: Final prediction results

1. Group dataset into 2 [training and testing dataset]. /*get the largest matrix eigenvectors and training data subsets*/
2. Obtain cluster center and result. /*We 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 data subsets are used to test corresponding sub-DNNs, based on each 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

Listing 1: The Energy Deep Learning Cluster (EnDeLClusE) Algorithm

3. RESULT FINDINGS & DISCUSSION

3.1 Review of Related Literatures

For efficiency and accuracy, we measure misclassification and corresponding improvement percentages for both training and test datasets as summarized in Tables 1 given by Eq. 3 and Eq. 4 respectively.

$$Misclassification\ Rate = \frac{No.of\ Incorrectly\ Classified\ Rules}{No.of\ Sample\ set} \quad (3)$$

$$Improvement\ Percentage = \frac{MR(A) - MR(B)}{MR(A)}\ x\ 100 \quad (4)$$

Table 1: Misclassification Rate and Improvement Percentage for Each model

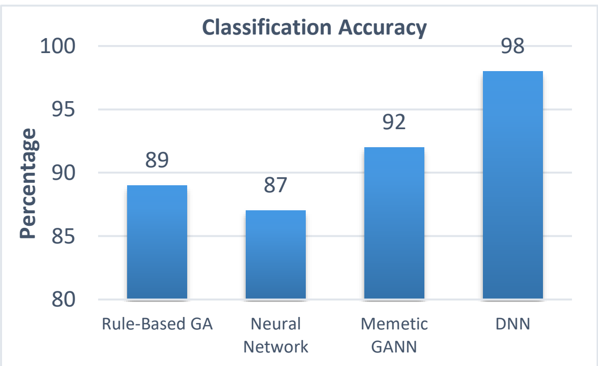
	Classification Errors		Improvement Percentages	
Model	*Training Data*	*Testing Data*	*Training Data*	*Testing Data*
Rule-Based GA	52.5%	23.2%	2.11%	3.6%
Neural Network (MLP)	48.4%	4.7%	2.32%	4.02%
Memetic (GANN)	19.6%	1.02%	0.09%	0.12%
DNN	1.23%	0.92%	0.09%	0.12%

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 Accuracy and Convergence Time

With the benchmark models (namely: genetic algorithm GA, neural network NN and memetic algorithm GANN), we seek to compare how well our proposed DNN performs as seen in fig 2. Results shows that DNN outperformed all the other models. We observed that a trade-off with the memetic GANN is the ability of the researchers to resolve conflicts with data encoding from GA to NN and resolving the conflicts of statistical dependencies imposed on the hybrid; and parameter selection. This was found to have contributed to the speed limitation – though its merit is in its greater flexibility, adaptation and robustness of the hybrid model.

For the mean processing time required to converge – it is found that GANN outperformed our proposed model. This can be attributed to the fact that: (a) the hybrid model needs to first use GA as pre-processor to train the Neural network, (b) though such hybrids has structural dependencies with the underlying heuristics employed and conflicts in data encoding that is required, it is worthy to note that DNN can be found to be slower in its processing time due to the amount of hidden layers embedded in such model.



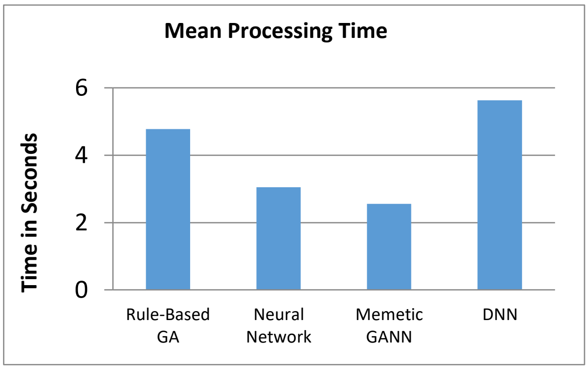


Figure 2: Comparative Accuracy of models

Figure 3: Comparative convergence Time

3.2 Accuracy and Convergence Time

Figure 4 show futures-price direction monthly forecast for 2019. Spot-price is the monthly average oil price (dollars/barrel) and its volatility is estimated from prices in previous year. For 2017, oil price volatility varies between 1.9012 and 0.312; For 2022, volatility varied between 0.16 and 0.3542. Thus, we expect that in the year 2023 – price direction volatility will vary between 0.412 and 2.092, for a 12-months period (52 weeks) futures maturity. Thus, the oil price is expected to still go up due with demand; Rather, than plummet in the near future. The results still holds same for Ojugo and Allenotor (2017), and for Ojugo and Otakore (2020). The price direction plummet may have been contributed by two (2) facts: (a) a change in condition due to the training of the model using older dataset, and (b) energy is about dominance and international politics plays a crucial role as displayed due to concerns, policies and vested interests. These, in time results in various shocks ranging from convenience yield, internal influences etc – to mention but a few (Khaki et al., 2020; Segarra et al., 2020; Zala & Chaudhari, 2018).

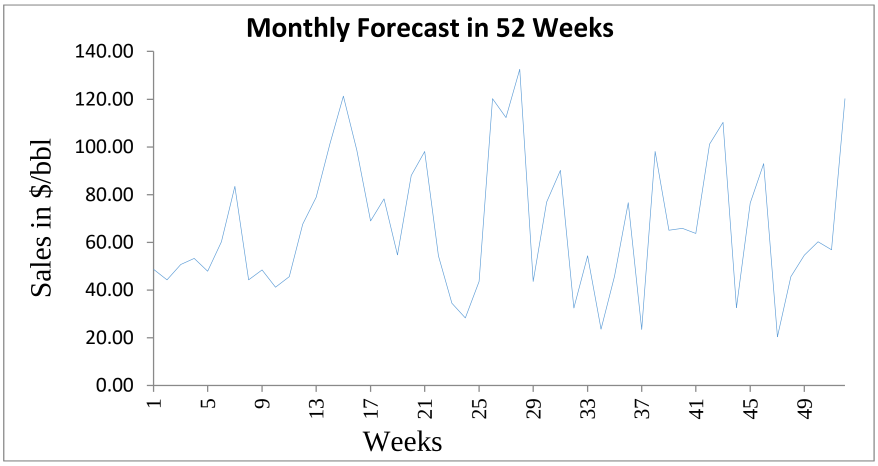


Figure 4: Futures Price volatility for 52-weeks

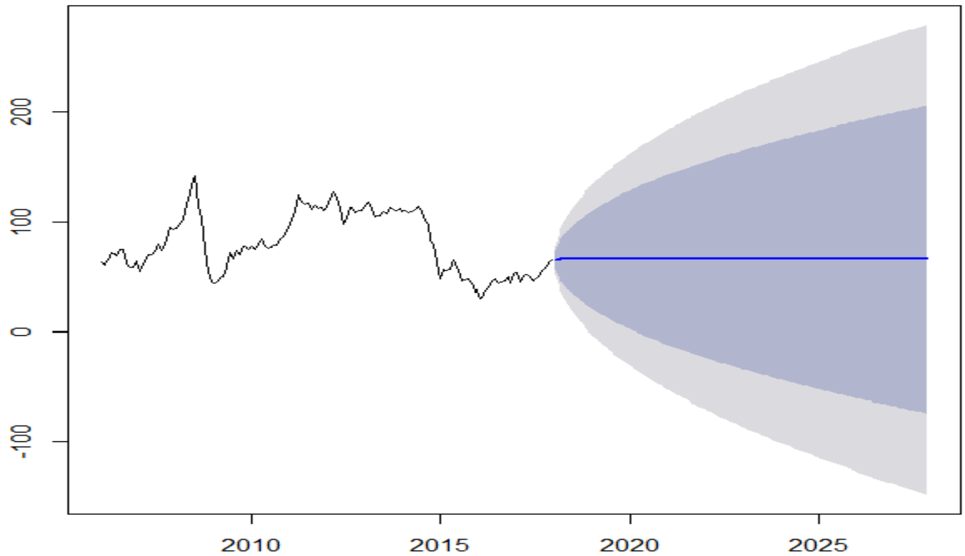


Figure 5: Predicted futures price direction from 2022 to 2025 (3-years projection)

Figure 5 shows the expected spot and futures-price direction monthly forecast for 2020 to 2025. The spot-price is the monthly average oil price (dollars/barrel) with volatility estimated from prices in previous year. For 2020, price volatility varies between 1.9012 and 0.312. For 2021, the price volatility varies between 0.16 and 0.3542; while for 2022 through to 2025, the price volatility varies from 0.412 to 2.092 for a 52-weeks futures maturity period. Thus, results shows that the price of oil will still go up due to demand from the OPEC and non-OPEC countries; Rather, than a plummet in the near future.

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 the price response behaves the same way. Thus, futures-price are informative insights about future-spot prices only – except when spot prices substantially exceed futures-price.

4. CONCLUSION

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, w1 = 0.2, w2 = 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.

Conflict of Interest

The authors declare that there is no conflict of interest.

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