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REVIEW ARTICLE

# SIMULTANEOUS PROJECTION OF WORLD MULTIPLE CRUDE OIL PRICE BENCHMARKS VIA HYBRIDE OF PARTICLE SWARM OPTIMIZATION-GRAVITATIONAL SEARCH ALGORITHM REDESIGNED NEURAL NETWORKS

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**ABSTRACT**

Conventional methods such as econometrical and statistical models are no longer feasible to handle the nonlinear, non-stationary, chaotic, volatile, and complex nature of crude oil prices due to their linearity nature; computational intelligence techniques were proposed to address these issues. More so, single modelling principle and traditional methods have not been effective enough in forecasting of crude oil prices, hybrid modelling principles have been employed to predict crude oil prices by researchers with better improvements. A group researchers opined that the use of hybrid models can also reduce the risk of choosing an inappropriate model because the use of a single model cannot always accurately forecast the extremely complex crude oil price time-series. A combination method can be applied to multiple forecasts and perform linear or nonlinear combinations of the forecasts, leading to an aggregate forecast. However, no research is found to have used the hybrid of gravitational search algorithm (GSA) and particle swarm optimization (PSO) to train artificial neural network (ANN) for simultaneous prediction of crude oil price benchmarks of WTI, Brent and Dubai. More so, most researchers have dwelled on only West Texas Intermediate (WIT) crude oil spot prices as their benchmark.

**KEYWORDS**

Econometrical and Statistical, Computational Intelligence, Forecast, Simultaneous

## 1. INTRODUCTION

Crude Oil is one of the most important and valuable natural resources in the world economy (Gabralla et al., 2013; Chiroma et al., 2016). Crude oil plays a paramount role in the world economy, useful to industries, governments and individuals and is said to be the life blood of world's economy (Azadeh et al., 2012; Gabralla et al., 2013; Gabralla et al., 2014; Mostafa and El-Masry, 2015; Kaur and Kaur, 2016; Gao and Lei, 2016). Nwulu asserted that no sector of the world doesn't feel the impact of crude oil price fluctuations (Nwulu, 2017). Crude oil is a kind of indispensable basic energy source, chemical material and strategic resource in socio-economic development (Zhang et al., 2015). Forecasting of oil price is a complex process and at the same time indispensible to the global economy (Wang et al., 2018). Complex features like nonlinearity, uncertainty, dynamism and world oil price fluctuations make forecasting more difficult (Safara and Davallou, 2018).

Since oil is a volatile commodity, its volatility depends upon various factors like, Gross Domestic Product growth,* stock levels inventories, foreign exchange rates, world population, and political aspects (Kaur and Kaur, 2016; Wang et al., 2018).The fluctuations of crude oil prices affect the economic growth of importing and exporting countries as well as regional security and stability. A rise or a fall in crude oil price, will lead to redistribution of wealth in both oil exporting countries and importing countries (Li et al., 2013; Fan et al., 2016; Naser, 2016; Gabralla et al., 2014). For investors who set foot in crude oil market, precise forecasting of the crude oil trend is of great importance to lower their investment risks, and generate more profits based on reliable prediction (Mei et al., 2015). Forecasting is about making claims on something that is going to happen. Forecasting is based upon information from past and current state. This prediction is also useful in order to make the economy of a nation to be stable (Fan et al., 2016; Thakur et al., 2016).

In the late1970s, oil price skyrocketed as a result of the anticipation shortages of future supply and rising global demand after the Iraq-Iran war (Cheng et al., 2018). It was from this time the international crude oil price has never being stable. Since then many researches have been conducted to investigate the underlying characteristics of crude oil price movement (Zhao et al., 2013). And since then conventional methods such as economical and statistical methods were the prevalent methods utilized in forecasting oil pricing. But because of the linearity of these methods, they are no longer feasible to handle the nonlinear, non-stationary, chaotic, volatile, and complex nature of crude oil prices; computational intelligence techniques were proposed to address these issues (Chiroma et al., 2016). Nature-inspired (NI)metaheuristic algorithms have become popular and powerful and with so many applications in computational intelligence (Yang et al., 2014).

Artificial neural network (ANN) is one of the most widely used nature inspired algorithms which have been used to predict crude oil prices in the 1980s (Wang et al., 2018). Studies such as Sompui and Wongsinlatam used ANN to predict crude oil prices and many studies have used ANN in combination with other nature inspired algorithms to predict crude oil prices (Sompui and Wongsinlatam, 2014; Mahdiani and Khamehchi, 2017; Chiroma et al., 2015; Chiroma et al., 2015; Chiroma and Abdulkareem, 2016; Mehrara et al., 2014; Chiroma et al., 2014). Kaur and Kaur (2016) made a survey of the researches for predicting crude oil price using ANN, and found that ANNs have gained popularity as an effective tool for

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forecasting purposes. Although, many researches have been proposed in the literatures for accurate prediction of crude oil prices, however, the accuracy of a prediction model is still an open research problem.

## 2. Literature Review

In the past years, NI algorithms have gained popularity in different fields of research for their good performance. Several real-world optimization problems have been studied by several NI algorithms (Adithyan et al., 2017). NI algorithms are considered as metaheuristic algorithms which are higher than heuristics and appropriate for NP-hard optimization problems. NI algorithms have been utilized by researchers to forecast crude oil predictions using single and hybrid modelling principles, with Sometimes, used to optimize certain characteristic of other models. Prediction of monthly prices of West Texas Intermediate (WTI) crude oil prices was presented (Chiroma et al., 2014). They proposed an orthogonal wavelet support vector machine (OSVM), unlike the previous work that used radial basis, sigmoid, polynomial, linear, and hyperbolic functions as the kernel function for computation in the neurons of conventional support vector machine (CSVM) model. Their proposed method was better than CSVM and multilayer perceptron neural network (MLPNN).

Mostafa and El-Masry proposed evolutionary techniques using gene expression programming (GEP) and ANNs models to predict oil prices (Mostafa and El-Masry, 2015). Their proposed model outperform the traditional statistical techniques of Autoregressive integrated moving average (ARIMA) models in predicting oil prices. More so, experiment demonstrated that GEP outperform both ANNs and ARIMA models. Sompui and Wongsinlatam proposed a crude oil price prediction model based on ANN and compared it with least square method (LSM) (Sompui and Wongsinlatam, 2014). The ANN of one - four hidden layers was found to be able to forecast better than the LSM. An adaptive neuro-fuzzy inference system (ANFIS) is developed to predict the oil prices of the organization of petroleum exporting countries (OPEC) (Lotfi and Karimi, 2014). Their experimental results show the superiority of their proposed method over the tradition NNs prediction model.

Yu, Zhang and Wang formed a study to verify the feasibility and potentiality of SVM in crude oil price Forecasting (Yu et al., 2017). They verified by comparing their proposed method with five other models such as feed-forward neural networks (FNN), ARIMA model, fractional integrated ARIMA (ARFIMA) model, Markov-switching ARFIMA (MS-ARFIMA) model, and random walk (RW) model. Better performance for crude oil price predicting in terms of either one-step prediction or multi-step prediction was achieved. Co-active neuro-fuzzy inference systems (CANFIS), a novel approach to crude oil prediction was presented (Chiroma et al., 2013). CANFIS demonstrated a high level of generalization capability with relatively very low error and high correlation which exhibited successful prediction performance of the proposal.

Single modelling principle and traditional methods have not been effective enough in forecasting of crude oil price, hybrid modelling principles have been employed by researchers with better improvements. The hybrid modelling principle works by combining different methods and taking full advantage of all the merits of the methods and leave out their shortcomings (Ding, 2018). Also, some group researhcer opined that the use of hybrid models can also reduce the risk of choosing an inappropriate model because the use of a single model cannot always accurately forecast the extremely complex crude oil price time-series (Fan et al., 2016). A study stated that the prediction of future crude oil prices is complex due to three characteristics of crude oil prices, namely, their lag, nonlinearity, and interrelationship among different oil markets, which is difficult to be solved simultaneously by most traditional crude oil price forecasting models, therefore, the authors proposed a new hybrid vector error correction and nonlinear autoregressive neural network (VEC-NAR) model to deal with these characteristics simultaneously (Cheng et al., 2017).

A group researcher proposed a novel model linking firefly algorithm (FA) with least squares support vector regression (LSSVR), called FA-LSSVR (Li et al., 2013). Performance is compared with other models, including hybrid intelligent methods e.g. PSO- LSSVR and single models with given predetermined parameters such as ARIMA and SVM, results shows FA-LSSVR is more robust. The random changes which is cause by the non-deterministic events causes the crude oil prices to fluctuates which can be referred to as noise which affect deterministic variations in prices, Behradmehr and Ahrari employed the wavelet transform as a tool for smoothing and minimizing the noise presented in crude oil prices (Behradmehr and Ahrari, 2014). GMDH neural network as the forecasting model. The effect of noise was minimized, and variance is captured by Auto-Regressive Conditional Hetroscedasticity model. Chiroma, Gital, Abubakar, Usman and Waziri proposed a hybrid approach combining GA and NN (GANN) to predict crude oil prices based on energy product prices (Usman and Waziri, 2014).

GANN compared with SVM, Vector Autoregression (VAR) and FFNN, result revealed the efficacy in the prediction accuracy and time computational complexity was improved and better. In order to improve the prediction performance, Yu, Zhao and Tang proposed the integration of compressed sensing based denoising (CSD) and certain artificial intelligence (AI), i.e., CSD-AIs to predict the WTI crude oil prices (Yu et al., 2014). CSD-AI learning paradigm significantly outperforms all other benchmark models including single models without CSD process and hybrid models with other denoising techniques, in terms of level and directional accuracies. A group researchers proposed ANFIS using PSO to predict the crude oil price of WTI (Gabralla et al., 2014). Proposed method performed better than the previous ones. A hybrid model integrating wavelet and multiple linear regressions (MLR) named WMLR was proposed by Mallat wavelet transform is first selected to decompose an original time series, the principal component analysis (PCA) is used in processing subseries data in MLR for the prediction and finally PSO was used to adopt the optimal parameters of the MLR model (Shabri and Samsudin, 2014). WMLR was better when compared with MLR, ARIMA, and GARCH.

A group researchers considered a combination of NN with three kinds of evolutionary algorithms (GA, imperialist competitive algorithm and PSO algorithm) (Mehrara et al., 2014). The research findings proved that, unlike other similar research, that combination of mix NN and evolutionary algorithms have not led to lower prediction error. Some researchers propose a support vector machine-based ensemble model to forecast crude oil price of WTI oil spot price ($(VECM+STEPMRS)_{SVM}$) (Xu et al., 2015). In the proposed model, VECM is first used to model the trend of crude oil price, and then STEPMRS is offered to forecast errors. Finally, SVM is employed to integrate the results from the ones of VECM and STEPMRS to make the final forecasting values more accurate and desirable. Chiroma and Abdulkareem considering the impact of uncertainties proposed a model based on a NN and GA (neuro-genetic) for the prediction of crude oil prices (Chiroma and Abdulkareem, 2016).

The model learn patterns from volatile crude oil price datasets that were distorted by the Gulf War, Asian financial crises, Iraq War, Venezuelan unrest and global financial crises. The proposed model was better in terms of both accuracy and CPU processing time compared with NN and SVM models. In a similar approach, GA and NN (GA-NN) were combined and studied for WTI crude oil price prediction (Chiroma et al., 2015). The proposed GA–NN is better than the ten (10) BP algorithms in the prediction Accuracy. Also, Mahdiani and Khamehchi modified NN modelling away that a GA optimizes its parameters during its run (Mahdiani and Khamehchi, 2017). Their model outperformed the pure NN especially in situation of small number of input data for training or the great changes of variables. A novel hybrid method to forecast crude oil prices was proposed by that combines ensemble empirical mode decomposition (EEMD) method, least square support vector machine together with the PSO (LSSVM–PSO) method and the generalized autoregressive conditional heteroskedasticity (GARCH) model are developed to decompose international crude oil price into a series of independent intrinsic mode functions (IMFs),forecast the nonlinear and time-varying components of crude oil prices, respectively (Zhang et al., 2015).

The hybrid method performed well in adaptation to the random sample selection, data frequency and structural breaks in samples. Variational mode decomposition (VMD)-based generalized regression neural network ensemble learning model was proposed (Lahmiri, 2017). In order to improve accuracy and convergence speed and to avoid local minima in NN, Chiroma et al (2015) employed a bio-inspired algorithm, called Flower Pollination Algorithm (FPA) to predict Dubai crude oil prices. Their proposed model, FPNN, performed better than the CSNN and ABCNN in terms of average CPU time and MSE. Kristjanpoller & Minutolo considered a hybrid of ANN-GARCH model (Kristjanpoller and Minutolo, 2016). And the precision of the price return volatility forecasting was better than GARCH and ARFIMA. Fan, Pan, Li and Li propose a novel ICA-based support vector regression scheme, namely ICA-$SVR^2$, the independent component analysis (ICA) decompose oil price series into three independent components then forecasted by SVM (Fan et al., 2016).

A group researchers proposed a deep learning ensemble approach using a deep learning NN called stacked denoising autoencoders (SDAE) which they used to model the non-linear relationships of oil prices and combined it with an ensemble method called boostrap aggregation (bagging) (Zhao et al., 2017). They compared their proposed model, SDAE-B, with other models such as SVM, FNN, SVM-B, FNN-B and SDAE. The turning points in international oil price are the most significant and sudden corrections in prices in the world market, proposed an improved version of log-periodic power law (LPPL) by embedding multi-population genetic algorithm (MPGA) to search the optimal values of parameters in LPPL method (Cheng et al., 2018). Their model outperformed other approach that combined LPPL based on SA, SGA and PSO in predicting the turning point of oil prices. Ding presented a novel decompose-ensemble prediction process combining the ensemble empirical mode decomposition (EEMD) and artificial neural network (ANN) named, EEMD-ANN-ADD (Ding, 2018).

Four steps in the model are; model selection via Akaike's information criterion (AIC), data decomposition via EEMD, individual prediction via ANN and ensemble prediction through addition ensemble method. Their experimental result showed that EEMD-based outperforms the empirical mode decomposition (EMD) based. They also proved that the "decompose-ensemble" model is better than the hybrid models in terms of accurate prediction. Huang and Wang proposed a prediction model based on wavelet neural network (WNN) and random time effect function (RT) called WNNRT (Wang, 2018). WNNRT compared with the traditional back propagation neural network (BPNN), SVM and WNN models, the empirical results demonstrate that the proposed model has a higher accuracy. It is important to combine different models and investigate different approaches, especially time-varying forms proposed a Hybrid forecasting model (PHM), based on exponential smoothing model (ESM), ARIMA and nonlinear autoregressive (NAR) neural network (Safari and Davallou, 2018). PMH recorded better performance to its constructive models, the equal weights hybrid model(EWH), the genetic algorithm weights hybrid model (GWH), and the Zhang's hybrid model (ZHM).

A group researchers opined that, currently the most popular and robust prediction methods are based on machine learning, such as ANNs, SVMs, and logistic regression (Mei et al., 2015). However, the representations of the data are also crucial to the performance of the classifier training. The authors then proposed non-negative matrix factorization techniques to capture the intrinsic features of the crude oil data. Then SVM is trained on the data in order to predict the tendency of crude oil future price. Their model is termed as NMF+SVM. Google trends data have been found helpful to enhanced better prediction of crude oil prices, improved through the use of Google trends data, the classification techniques of LogR, BPNN, DT and SVM and the forecasting techniques of LR, ELM, BPNN and SVR for oil consumption prediction, in terms of both directional and level accuracy (Yu et al., 2018).

## 3. Methodology

This research proposes a methodology that implements a hybrid of Particle Swarm Optimization and Gravitational Search Algorithm, PSOGSA in training Artificial Neural Network, ANN for the simultaneous prediction of Brent, Dubai and WTI crude oil price benchmark. The fundamental idea of PSOGSA is to put together the social thinking (gbest) ability in PSO with the local search capability of GSA. To enable combination of these algorithms, the following is proposed:

$V_i(t+1) = w\times V_i(t) + C_1' \times rand \times ac_i(t) + C_2' \times rand \times (gbest - X_i(t))$

Where $V_i(t)$ is the velocity of agent *i* at iteration *t*, $C_j'$ is a weighing factor, *w* is a weighing function, rand is a random number between 0 and 1, $ac_i(t)$ is the acceleration of agent *i* at iteration *t*, and *gbest* is the best solution so far.

In each of the iteration, update on position of particles are given as follows:

$X_i(t+1) = X_i(t) + V_i(t+1)$

In PSOGSA, all agents are, at first randomly initialized. Where each of the agents seen as an individual solution. After initialization, Gravitational force, gravitational constant, and resultant forces among agents are calculated using the following:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t)M_{aj}(t)}{R_{ij}(t)+\varepsilon}(x_j^d(t) - x_i^d(t))$$

$$G(t) = G_0 e^{-\alpha\frac{t}{T}}.$$

$$F_i^d(t) = \sum_{\substack{j=1\\ j\neq i}}^{N} randF_{ij}^d(t),$$

Thereafter, the accelerations of particles are defined as

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)},$$

The best solution so far is updated in each iteration. After calculating the accelerations as well as updating the best solutions so far is done, the velocities of all agents can then be calculated using

$V_i(t+1) = w\times V_i(t) + C_1' \times rand \times ac_i(t) + C_2' \times rand \times (gbest - X_i(t))$

Finally the positions agents are defined as

$X_i(t+1) = X_i(t) + V_i(t+1)$

Only after meeting up with an end criterion can the process of updating velocities and positions be stopped. The steps of PSOGSA are represented as seen in the figure 1 below.

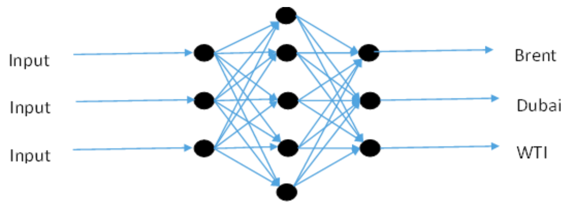


**Figure 1:** Model Neural Network for Hybrid PSOGSA

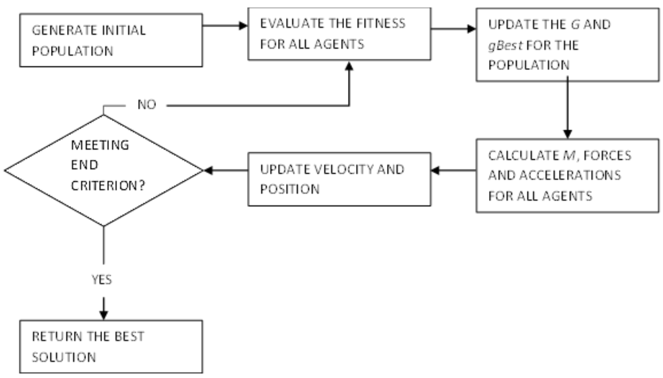


**Figure 2:** Steps of PSOGSA

The following remarks should be noted in understanding how efficient PSOGSA is. The quality of solutions (fitness) in PSOGSA is considered in the updating procedure. Also, the agents that are near good solutions try to attract other agents which are exploring the search space. Furthermore, when all agents are near a good solution, they move very slowly. In this instance, the gBest help the agents to exploit the global best. PSOG uses a memory (i.e gBest) to save the best solution found so far, so that it can be accessible at any time. Noteworthy is that each agent can observe the best solution so far and move towards it. The abilities of global search and local search can be balanced with adjusting $C_1'$ and $C_2'$ (Mirjalili and Hashim, 2010).

## 4. Performance Evaluation and Results

The developed models had seven input neurons, fifteen hidden neurons and one output. The models were trained with PSOGSA, Levenberg-Marquardt, Bayesian regularization and BFGS quasi-Newton Back propagation algorithms. The training performances are shown in Table 1 and 3 respectively.

**Table 1:** Training Performance Results of Four Models of Brent Benchmark.

| Model | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Architecture | 7-15-1 | 7-15-1 | 7-15-1 | 7-15-1 |
| Hidden Neurons | 15 | 5 | 5 | 5 |
| Training Algorithm | PSOGSA | Levenberg- Marquardt | Bayesian regularization | BFGS quasi-Newton |
| Training MSE | 7.13E-32 | 0.0241 | 0.0223 | 0.0399 |

Table 1 shows the performance of four models with the corresponding architectures, number of hidden neurons, training algorithms, training MSE and RMSE values. The first model has seven input neurons, fifteen hidden neurons and one output neuron. The first model was trained with Particle Swamp Optimization -Gravitational Search Algorithm (PSOGSA) to obtain a training MSE of 7.13E-32.

The second model has seven input neurons, five hidden neurons and one output neuron. The second model was trained with Levenberg- Marquardt Backpropagation Algorithm (trainlm) to obtain a training MSE of 0.0131.

The third model has seven input neurons, five hidden neurons and one output neuron. The third model was trained with Bayesian regularization Backpropagation Algorithm (trainbr) to obtain a training MSE of 0.032.

The fourth model has seven input neurons, five hidden neurons and one output neuron. The fourth model was trained with BFGS quasi-Newton Backpropagation Algorithm (trainbfg) to obtain a training MSE of 0.032 and a corresponding RSME of 0.24.

From Table 1 above the first model trained with PSOGSA has the lowest training MSE of 7.13E-32 indicating a good training performance compared with the other models.

**Table 2:** Performance results of four Models of WTI Benchmark.

| Model | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Architecture | 7-15-1 | 7-15-1 | 7-15-1 | 7-15-1 |
| Hidden Neurons | 15 | 15 | 15 | 15 |
| Training Algorithm | PSOGSA | Levenberg- Marquardt | Bayesian regularization | BFGS quasi-Newton |
| Training MSE | 3.76E-28 | 0.0127 | 0.0182 | 0.0157 |

Table 2 above shows the training performance of four models developed and trained with the crude oil data set as inputs and the WTI data set as the target data set. The models have the same architecture of seven input neurons, fifteen hidden neurons and one output neuron. The following algorithms were used to train the models which are: PSOGSA, Levenberg-Marquardt, Bayesian regularization and BFGS quasi-Newton respectively. From Table 1.2 the first model has a training MSE of 3.76E-28 which is the lowest value indicating good training for the neural network.

**Table 3:** Training Performance Results of Four Models of Dubai Benchmark.

| Model | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Architecture | 7-15-1 | 7-15-1 | 7-15-1 | 7-15-1 |
| Hidden Neurons | 15 | 15 | 15 | 15 |
| Training Algorithm | PSOGSA | Levenberg- Marquardt | Bayesian regularization | BFGS quasi-Newton |
| Training MSE | 1.44E-20 | 0.0121 | 0.0178 | 0.015 |

Table 3 above shows the training performance of four models developed and trained with the crude oil data set as inputs and the Dubai data set as the target data set. The models have the same architecture of seven input neurons, fifteen hidden neurons and one output neuron. The following algorithms were used to train the models which are: PSOGSA, Levenberg-Marquardt, Bayesian regularization and BFGS quasi-Newton respectively. From Table 1.3 the first model trained with PSOGSA has the lowest training MSE of 1.44E-20 indicating good training for the neural network.

The FNNPSOGSA model has a low training MSE of 7.13E-32, 3.76E-28 and 1.44E-20 from Table 1, Table 2 and Table 3 respectively which show that there is no overfitting of the network model after training.

### 4.1 Discussion

The model has three layers which are input, hidden and output layers with seven input neurons, fifteen hidden neurons and one output neurons.

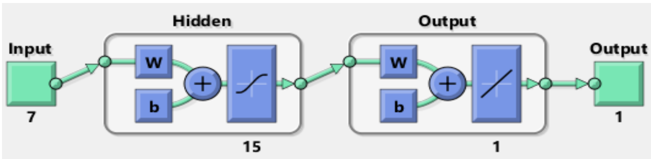


**Figure 3:** Feed Forward Neural Network.

#### *4.1.1 Training Analysis of Forecasted Result*

The number of function evaluations was at 500 and the best function value found was: 7.1312E-32 for the Brent Benchmark model in Figure 4 below. Figure 5 shows the training performance of the WTI benchmark with 500 iterations and 3.76E-28 best function value. The best function value of 1.44E-20 was obtained after 500 iterations (training epoch) for the Dubai benchmark model as shown in figure 6 below.

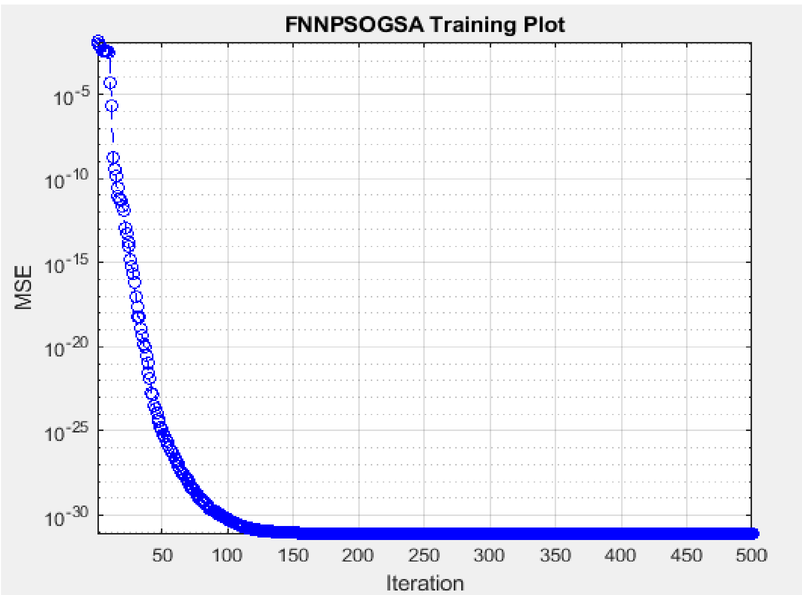


**Figure 4:** FNNPSOGSA Training plot for Brent Benchmark.

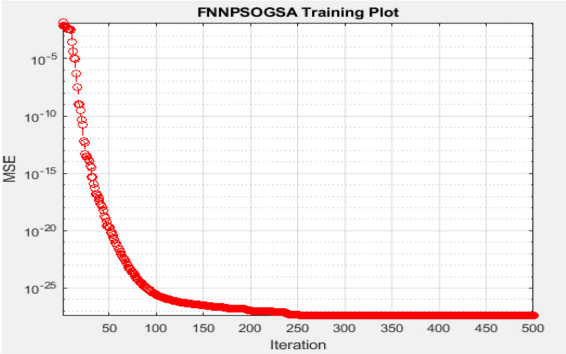


**Figure 5:** FNNPSOGSA Training plot for WTI Benchmark.

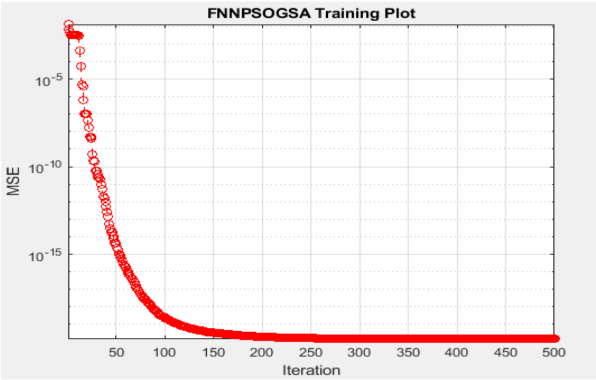


**Figure 6:** FNNPSOGSA Training plot for Dubai Benchmark

### 4.2 The Forecasted Output

The projected and actual crude oil prices benchmarks for Brent, WTI and Dubai benchmarks are shown in Figure 7, Figure 8 and Figure 9 respectively.

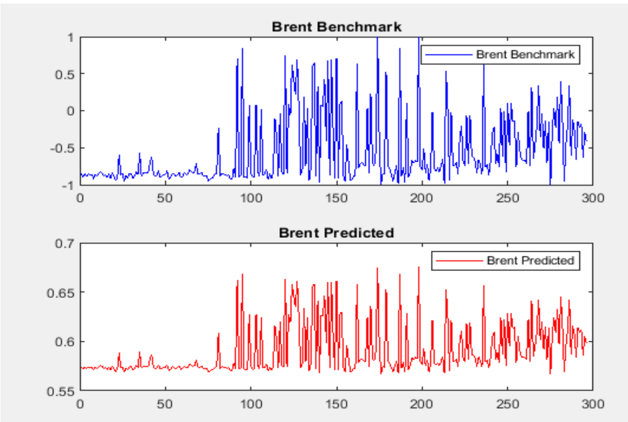


**Figure 7:** The Original and projected Brent Benchmark.

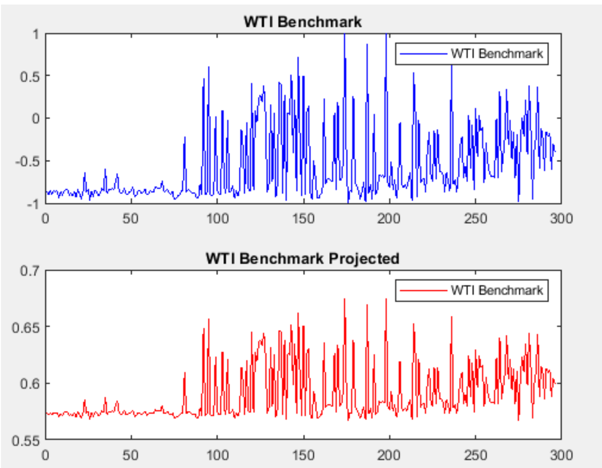


**Figure 8:** The Original and projected WTI Benchmark.

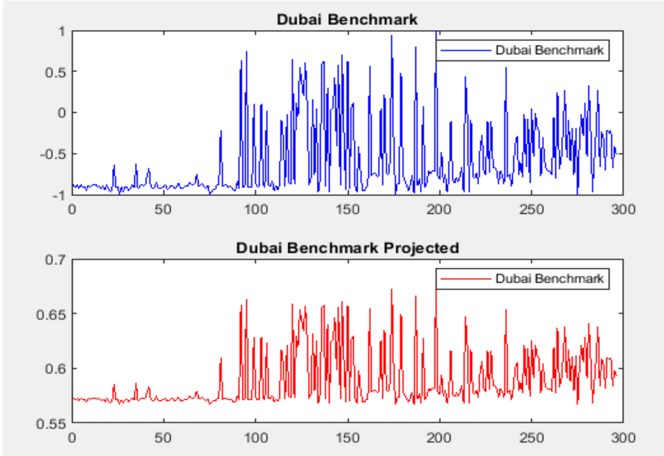


**Figure 9:** The Original and projected Dubai Benchmark.

From figure 7, 8 and figure 9 the projected benchmarks are identical with the original benchmarks for Brent, WTI and Dubai crude oil prices. The deviations between the original and projected benchmarks are due to other exogenous independent variables that affect crude oil prices benchmarks such as political climate of Oil producing and oil quota from OPEC.

As a result of the data analyzed, the findings of the study are as follows.

i. FNNPSOGSA Network is a suitable tool for projecting forecasting Crude oil Benchmark when trained with adequate data set.

ii. The Training MSE of the Brent , WTI and Dubai models were 7.1312E-32, 3.7614E-28 and 1.4371E-20 respectively.

iii. The RMSE of the Brent, WTI and Dubai models were 2.63, 2.80 and 2.73 respectively.

Inspired by the need to improve the decision making in the Oil industries shows that the result obtained using PSOGSA to train Feed Forward Neural Network (FNN) was within acceptable limits. The result of this study is in line with confirms the ability of PSOGSA algorithm in developing non-linear systems for classification and forecasting purposes (Mirjalili et al., 2012; Gajbhiye et al., 2019).

## 5. Conclusion

Crude Oil prices benchmark projection making remains an important function of managers in Oil companies and Government regulatory bodies. Managers need to use state of the art tools to enhance decisions making in order to maximize profit in Oil companies. The use of PSOGSA in projecting crude oil prices benchmarks has proved to be a veritable tool since crude oil prices pattern is highly complex and are affected by various extraneous factors such as politics and economic elements which makes crude oil prices benchmark projection a challenging task. The FNNPSOGSA algorithm was proposed to project crude oil benchmark by using crude oil benchmark data set. The model developed in this research was trained using epoch of 500 to avoid overfitting. The network was trained with PSOGSA algorithm to achieve low generalization error with accurate estimates. The result obtained justified the use of PSOGSA hybrid global search algorithms in projecting crude oil prices.

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