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Oil Consumption Prediction of OPEC Member States using Artificial Neural Network

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***Abstract* – In this study five Artificial Neural Network (ANN) models namely Back propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), Least Squares Support Vector Machines (LSSVM), Generalized Regression Neural Network (GRNN) and Group Method Data Handling (GMDH) were developed to predict oil consumption of the Organization of Petroleum Exporting Countries (OPEC) and their predictive performance were compared. The results of the study showed that, RBFNN model out performed all the developed models with MSE, VAF, PI, MSE values of 0.00707, 82.8538,0.85038,3.9899 and 1.532 respectively. The performance of the RBFNN was closely followed by GMDH, BPNN, LSSVM and GRNN. Based on the results of the Sobol's sensitivity analysis, values of oil export was the most influential factor that affects oil consumption of OPEC member states.**

***Keywords* – Artificial Neural Network, Oil Consumption, Macroeconomic Indicators, OPEC.**

I. Introduction

Oil is an essential component of an economy's production processes [11]. Similar to other primary commodities, oil price volatility affects price levels since it plays a key role in industrial production [11]. Unarguably one of the most important global macro indicators is the price of oil [8]. Oil price volatility affects economic processes, inflation and movements of currencies [6]. Oil still remains the primary source of energy despite more aggressive climate goals on the usage of renewable energy [5]. The most critical factor that affects oil price volatility is the demand and supply of oil [1]. Globally, energy consumption is rapidly increasing due to high population growth rate, persistent pressures for higher standard of living and focus on large scale industrialization in developing countries in order to boost economies and sustain positive economic growth.

The organization of Petroleum Exporting Countries (OPEC) is a cartel of oil producing states with fifteen member states namely Algeria, Angola, Congo, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Libya, Nigeria, Quatar, Saudi Arabia, United Arab Emirates and Venezuela. The organization plays a key role in supplying oil to many countries across the globe [2]. Five OPEC countries are among the top five countries in the world in terms of proven oil reserves and supplies about 40% of the total global oil [9]. OPEC has played a vital role in fueling the world's economic activities in previous decades [9].

However, Oil consumption rate of OPEC has increased, OPEC consumes approximately 20% of its quantity of total oil produced [2]. OPEC's ability to increase oil exports to other countries that rely on the bloc for their oil needs could be hampered by the bloc's increasing oil consumption rate [2]. In order to prevent global oil supply and demand imbalances, oil consumption prediction is required in order to ensure proper management of supply and demand, investment analysis, analysis of revenue generation and management of research related to energy [2]. Accurate oil consumption prediction is vital for the production and distribution of oil in order to prevent global oil supply and demand imbalances.

A plethora of methods have been used in literature for oil consumption prediction. According to Debnath and

Mourshed [3] the methods used in literature for oil consumption prediction modelling are statistical and computational intelligence. Within the statistical methods division are Time series analysis, Autoregressive Conditional Heteroscedascity and Grey models and within the class of computational Intelligence are Machine Learning (ML), Metaheuristics and Expert-based methods.

Using classical statistical methods, Yuan et al, (2016) [20] predicted the oil consumption of China using ARIMA model and the grey model to predict the oil consumption of China and their prediction performance was compared. The results of the study revealed that the ARIMA responded to less fluctuation since it was bounded by its long-term trend. Orurk and Ozturk (2018) [10] used ARIMA model to predict the consumption of oil, coal, natural gas and renewable energy. The ARIMA models developed were ARIMA (1, 1, 1), (0, 10) and (0, 1, 2) respectively. Based on the results of the study, oil, consumption will keep increasing on yearly basis at the rate of 3.92%. Duan et al (2018) [4] predicted oil consumption of China using grey prediction models. The results of their study showed that grey model was able to accurately predict the oil consumption of China.

Togun and Baysec [15] developed an ANN model for the prediction of torque and brake specific oil consumption. The results of the study showed that the ANN with architecture 3-13-1 and 3-15-1 were the optimal models for the developed Torque and Brakes specific oil consumption models. Using ANN Kieh-Kim et al [7] developed a BPNN based decision support system for ship fuel consumption prediction. Historical data of vessel of vessel operations were used for the study. The input variables used for the study were GPS position, Course over Ground, Speed over Ground, Balance of the Vessel, Wind Direction, Vessel Inclination, Acceleration and shift Power. To investigate the relationship between the input variables and the ship fuel consumption the ANN model was developed and compared with Multiple Linear Regression. The developed ANN model provided a better fit with R^2 and Mean Absolute Percentage Error of 0.9250 and 19%.

Chiroma et al [2] carried out the first study in developing predictive models for OPEC oil consumption using metaheuristic techniques using Flower Pollination Algorithm. The data set used in the study was yearly oil consumption of OPEC member states, in the end it was realized that the proposed FPA-ANN model outperformed the GA, ABC and PSO-ANN models in terms of convergence speed forecasting accuracy and robustness.

The peculiarity of energy consumption prediction is the presence of multidirectional trends, seasonal and cyclical fluctuations and structural brakes. Certain assumptions are required to be met when using the classical statistical methods. A significant advantage of ANN model is their ability to model non-linear relationships not restricting on stationarity of the parameters providing an ideal approximation of actual and predicted. ANN is a powerful modeling tool that has the ability to identify complex relationship from input-output data. In contrast with conventional models, AI-based forecasting models do not rely on explicit relationship between energy consumption and its influencing factors but rather learns form large amount of historical data. Also due to irregular patterns of energy demand data, statistical techniques have limited performance.

In this study five Artificial Intelligence (AI) models have been developed to predict the oil consumption of OPEC using their macroeconomic indicators of OPEC as input variables. With the goal of increasing the scope of AI applications in energy demand modelling, this study compares the capabilities of five of the most widely used AI methods in predicting OPEC oil consumption of OPEC member states.

II. Data Description

Secondary data of macroeconomics indicators namely Real Gross Domestic Product (GDP) per capita, Population Growth, Oil Prices, Oil Production, Values of oil Export, Values of Imports and Population Growth were sourced from OPEC website (Data download opec.org). The data used constitute annual time series data from 1960 to 2019. The choice of these macroeconomic indicators was strictly based on the general energy demand model which specifies demand as a function of price, real GDP per capital, population growth and production and the availability of data the description of the basic features of OPEC macroeconomic indicators used in the study is shown in Table 1. It provides simple summaries about the data.

Table 1. Descriptive statistics of macroeconomic data of OPEC.

Parameter	Minimum	Maximum	Mean	Standard Deviation
GDP	26000	3.40 x 10^6	9.40 x 10^5	1 x10^6
Real GDP	-6.70	13.3	3.80	4.60
Values of Export	6500	1.50 x 10^6	3.70x 10^5	4.50 x10^5
Values of Oil Export	4700	1.10 x 10^6	2.70 x 10^5	3.00 x10^5
Values of Imports	4200	9.10 x 10^5	2.40 x 10^5	2.80 x 10^5
Oil Production	300 x 10^7	5.4 x 10^8	2.60 x10^8	2.80 x 10^5
Population Growth	1.48	1.96	2.53	1.50 x 10^8
Oil Prices	109	1.75x 10^3	36.4	29.3
Oil Consumption	8800	2.40 x 10^5	3.90 x 10^3	2.80 x 10^3

III. Methods Used

A. *Data Normalization*

Since the data set used in the study constitute different values and different measuring units, it was crucial to ensure that the data set are put into a common scale. Data normalization minimizes the likelihood of getting stuck at local minimum and thus it enhances the rate of convergence [21]. In literature the common and widely used transformation criteria is [-1, 1]. In this study the data set was normalized by using equation (1).

Where y_i , X_i, X_{min} ,X_{max} denote the normalized data, the macroeconomic indicators of OPEC used in the study, the maximum and minimum values of the macroeconomic indicators with y_{max} and y_{min} set at 1 and -1 respectively.

$$y_i = y_{min} + \frac{(y_{max} - y_{min})\times(X_i - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

B. *Back Propagation Neural Network (BPNN)*

Rumelhart et al. [13] proposed the back propagation learning algorithm. Ever since it was introduced, it has become well-known ANN learning algorithms. BPNN uses the gradient-decent search approach to alter the connection weights throughout the learning phase to reduce the inaccuracy of ANNs. Figure 1 depicts the structure of a Back propagation ANN.

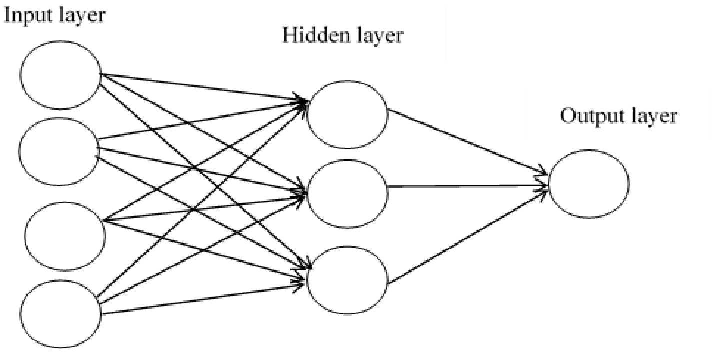

Fig. 1. Structure of a Back propagation ANN.

BPNN has been applied in diverse fields such as pattern recognition, location selection and performance evaluation [13]. Each neuron's output is the sum of the previous level's number of neurons multiplied by the appropriate weights. Activation functions are utilized to transform, the input values into output signals the BPNN consists of the input, hidden and output layer. The network's input is stored in the input layer the hidden layer is between the input and output layers. They act as a point of propagation for data from the previous layer to the next layer [12]. The output y_j is computed as a function of the sum f expressed mathematically in Equation (1) as,

$$y_j = f\left(\sum_{i=1}^{n} w_{j_i} x_i\right) \tag{2}$$

where f is the activation function, w_{j_i} is the weight and x_i is the input signal. The BPNN follows the error correction learning rule.

C. *Radial Basis Function Neural Network (RBFNN)*

The radial basis function neural network is based on the function approximation theory. It consists of an input layer, a hidden layer and an output layer as shown in Figure 2. In the computation process of RBFNN input signals are sent directly to the hidden layer without weighting. In the hidden layer each node stands for a radial basis activation function that is featured in vector space and a radial basis activation function is used as an excitation function. Figure 2 shows the structure of the RBFNN.

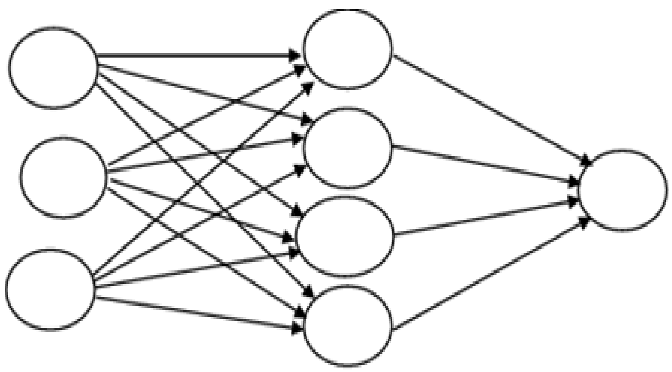

Fig. 2. RBFNN Architecture.

The following are some of the most widely used RBF transport layer functions: Thin Splate Spin,

$$\varphi(X) = X^2 \lg(X) \tag{3}$$

Multiple Quadratic Function,

$$\varphi(X) = (X^2 + c)^{\frac{1}{2}}, c > 0 \tag{4}$$

Gaussian Function,

$$\varphi(X) = exp\left(-\frac{|X - c_j|}{2\sigma_j^{\ 2}}\right) \tag{5}$$

Where c_j represent the center of RBF and σ denotes the width parameter which can modify the sensitivity of the RBF. The RBF layer transfer function is generally a Gaussian function and the output function is,

$$y_i(X) = \sum_{j=1}^{M} w_{ij}\ exp\left(-\frac{|X - c_j|}{2\sigma_j^{\ 2}} + b_j\right) \qquad i = 1,2 \ldots\ldots n \tag{6}$$

In this study, the widely used Gaussian activation function was employed in the hidden layer to process the data,

$$\alpha_j = f(x_i) = exp\left[\frac{[x - c_j]}{2\sigma_j^{\ 2}}\right] \tag{7}$$

Where α_j values are outputs of the radial function, $|x - c_j|$ is the distance between the feature vector$x$ and the center vector c_j.

The value of $|x - c_j|$ can be expressed as,

$$|x - c_j| = \sqrt{\sum_{i=1}^{m}(x_j - c_{ij})}\ i = 1,2 \ldots\ldots m \tag{8}$$

D. *Least Squares Support Vector Machines (LSSVM)*

The LSSVM is a modification of SVM introduced by Suyken (2000) [14]. The LSSVM outperforms the standard SVM in terms of accuracy by transforming a quadratic optimization problem into systems of linear equations [17]. The LSSVM predictor is trained using a single output as the target value and a set of time series history values as inputs. The LSSVM can be used to identify the best non-linear regression function [17].

$$minR(w, e) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{n} e_i^{\ 2} \tag{9}$$

Subject to the equality constraints,

$$y(x) = w^T \emptyset(x_i) + b + e_i\ i = 1,2 \ldots n \tag{10}$$

In order to solve the optimization problem, the Lagrande function is used,

$$L(w, b, e, \alpha) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{n} e_i^{\ 2} - \sum_{i=1}^{n}\alpha_i \{w^T \emptyset(x_i) + b + e_i - y_i\} \tag{11}$$

By partially differentiating the solution with respect to w, b , e_i and α_i yields the solution to equation,

$$\frac{\partial L}{\partial w} = 0\ implies\ w = \sum_{i=1}^{n}\alpha_i\ \emptyset(x_i) \tag{12}$$

$$\frac{\partial L}{\partial b} = 0\ implies\ \sum_{i=1}^{n}\alpha_i = 0 \tag{13}$$

$$\frac{\partial L}{\partial e_i} = 0\ implies\ \alpha_i = \gamma e_i \tag{14}$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \; implies \; w^T \emptyset(x_i) + b + e_i - y_i = 0 \quad (15)$$

The solution is obtained by the following set of linear equations after e_i an0d w_i have been eliminated.

$$\begin{bmatrix} 0 & 1^T \\ 1 & \emptyset(x_i)^T \emptyset(x_j) + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \quad (16)$$

$$y(x) = \sum_{i=1}^{n} a_i K(x_i, x) + b \quad (17)$$

As a result, the LSSVM model for function estimation is obtained Equation (17)There are several kernel functions for the LSSVM namely linear, polynomial, radial basis function and sigmoid.

E. *Generalized Regression Neural Network (GRNN)*

GRNN is often utilized for function approximation. It can approximate hidden function relationship using sample data because of its strong mapping capability and robustness. It consists of four layers namely the input layer, pattern layer, summation and output layer. Without employing any function operators, the output layer is responsible for transmitting input variables to the hidden layer. The hidden layer is used for the calculations of variables. The output of GRNN can be calculated using Equation 18 and 19.

$$d_i = (x - x_i)^T (x - x_i) \quad (18)$$

$$\hat{Y}(x) = \frac{\sum_{i=1}^{n} y_i \, exp\left(\frac{-d_i}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(\frac{-d_i}{2\sigma^2}\right)} \quad (19)$$

where d_i is the Euclidean distance between the input x_i and the training sample input, y is the training sample output and σ is the smoothing parameter of GRNN. This study investigated the strength of GRNN approach to predicting OPEC oil consumption.

F. *Group Method Data Handling (GMDH)*

The group method of data handling (GMDH) is a set of inductive methods for mathematical modeling of multi-parametric datasets that offer fully automated structural and parametric model optimization. A model can be represented as a set of neurons using the GMDH algorithm, with distinct pairings of neurons in each layer connected by a quadratic polynomial as a result, additional neurons are produced in the next layer. In each layer, a variety of intermediate variables are combined to create the best neuron architecture [20]. Output of previous layer serves as intermediate variable. To ensure that inputs are mapped into outputs in modelling such representation is used. As such the minimization of the difference between actual output and the predicted is required [16]. Though there are many techniques that can be used to achieve this, the Kolmogorov Gabon Polynomial or Volterien series is usually used (Equation 20).

$$y = a_o + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \quad (20)$$

A system of quadratic polynomial represents this full form of mathematical equation by only two variables (neurons) in the form,

$$\hat{y} = G(x_i, x_j) = a_o + a_1 x_1 + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \quad (21)$$

G. *Performance Indicators*

Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Variance Accounted for (VAF), Correlation Coefficient ((R^2) and Performance Index are the performance indicators used in the study to compare the performance of the developed models. The mathematical expression for these performance indicators is provided in Equation (22) to Equation (26).

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \tag{22}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \tag{23}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{P}_i)^2} \tag{24}$$

$$VAF = \left[1 - \frac{Var\,(O_i - P_i)}{Var\,(O_i)}\right] \times 100 \tag{25}$$

$$PI = \left[R^2 + \left(\frac{VAF}{100}\right)\right] - NRMSE \tag{26}$$

where O_i is the observed value and n is the number of fitted point. $\overline{P}_i$ is the mean of the predicted values and NRMSE (Normalised Root Mean Square Error) is computed using Equation (27).

H. *Sensitivity Analysis*

In order to determine the relative influence of the input parameters on the model's output, sensivity analysis was carried out. In this study the Sobol's sensitivity. Sobol's variance-based sensitivity method [18] was used to quantify how a model's outputs variance is explained by its input variance. The sensitivity indices (Equation (16)) range from 0 to 1. Si is the sensitivity index and is given as,

$$S_i = \frac{V_i}{V(Y)} \tag{27}$$

where Si is the sensitivity index, V_i is the induced conditional variance of due to factor i and $V(Y)$ is the unconditional variance of model output. The second order sensitivity index Sij is given as,

$$S_{i_j} = \frac{V_{i_j}}{V(Y)} \tag{28}$$

where V_{i_j} is the conditional variance due to factors i and j.

III. Main Result

A. *BPNN Model for OPEC Oil Consumption Prediction*

Table 2 shows the results of the performance indicators for the optimal BPNN model for the developed BPNN and Table 3 shows the performance indicators for the optimal BPNN model. As shown in the table 2 the MSE, VAF, R^2, MAPE and PI for the BPNN model were 0.00256, 99.92942, 34.54012, 1.990604 for the training data set and 0.074666, 13.06864, 0.377455, 13.3286 and 0.03108 respectively. It was observed in the training of the BPNN model that the network architecture [7-6-1] was the most optimal BPNN model with the least MSE, MAPE values and highest R^2 and PI values. The observed and predicted testing results for the optimal BPNN model is shown in Figure 3,

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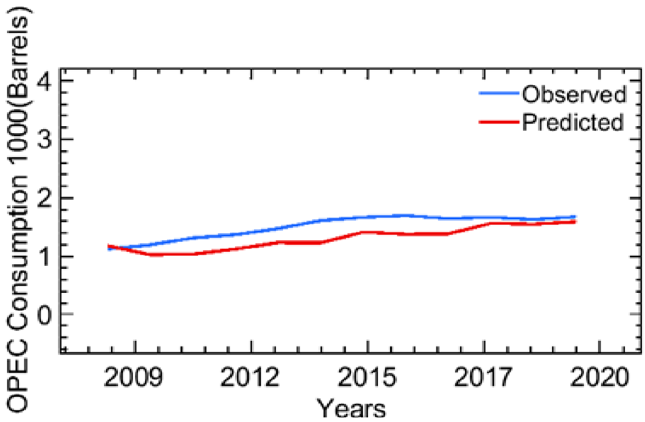

Fig. 3. Testing data prediction results for the optimal BPNN model.

Table 2. Optimal BPNN training results.

BPNN	Training				
	MSE	VAF	R^2	MAPE	PI
	0.00256	99.92942	0.999314	34.54012	1.990604

Table 3. Optimal BPNN testing results.

BPNN	Testing				
	MSE	VAF	R^2	MAPE	PI
	0.074666	13.06864	0.377455	13.3286	0.03108

B. *GRNN Model for OPEC oil Consumption Prediction*

Table 4 summarizes the results obtained from using the GRNN technique in predicting OPEC oil consumption. The performance metrics is shown for both training and testing phase. Equivalent to RBFNN, the smoothing parameter which is the only adjustable parameter was varied from 0.1 to 3 to allow for closer fit of the measured data. The smoothing parameter value of 0.2 recorded the best training performance metrics but failed to generalize appropriately on the testing data which indicate an over fitting condition. Therefore, the smoothing parameter value of 0.4 which performed considerably well at the training stage and was able to correctly adapt to the testing data was chosen as the GRNN best performing model. That is, the smoothing parameter recorded MSE, VAF, VAF, R^2, and PI values of 0.3170827, 3.241269, 0.037512, 31.48533 and 1.760604. Figure 4 shows the observed and predicted test results for the optimal GRNN model.

Table 4. Training result for GRNN.

GRNN	Training				
	MSE	VAF	R^2	MAPE	PI
	0.0377772	89.59804	0.961799	283.2946	1.760604

Table 5. Testing result for GRNN.

GRNN	Testing				
	MSE	VAF	R^2	MAPE	PI
	0.3170827	3.241269	0.037512	31.48533	-0.91318

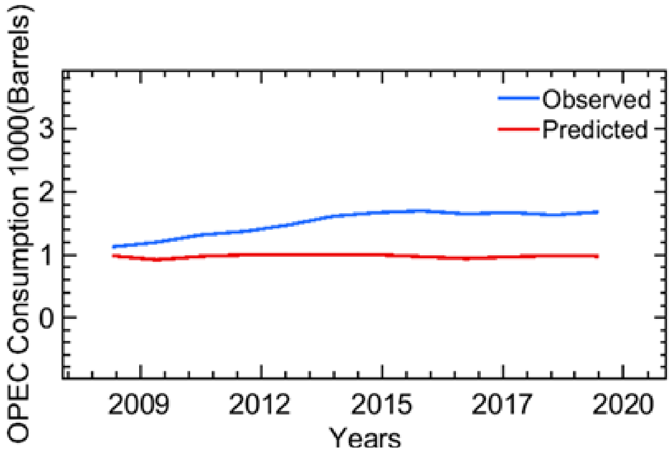

Fig. 4. Testing data prediction results for the optimal BPNN model.

C. *RBFNN Model for OPEC oil Consumption Prediction*

The optimal RBFNN model recorded MSE, VAF, R^2, MAPE and PI values of 0.007072, 82.85381, 0.850379, 3.7894 for the testing datasets and 0.00157, 82.854, 0.9956, 46.6043 and 1.991575 for the training data sets. The coefficient of determination gives an indication of the proportion of variance in the dependent variable that is explained or predicted by the independent variable. The smooth parameter was set in the range [0.1, 3] to allow for a better RBFNN approximation. The observed and predicted testing results for the optimal RBFNN model is shown in Fig. 5.

Table 6. Training result for RBFNN.

RBFNN	Training				
	MSE	VAF	R^2	MAPE	PI
	0.00157	82.854	0.9956	46.6043	1.991575

Table 7. Testing result for RBFNN.

RBFNN	Testing				
	MSE	VAF	R^2	MAPE	PI
	0.007072	82.85381	0.850379	3.7894	1.53209

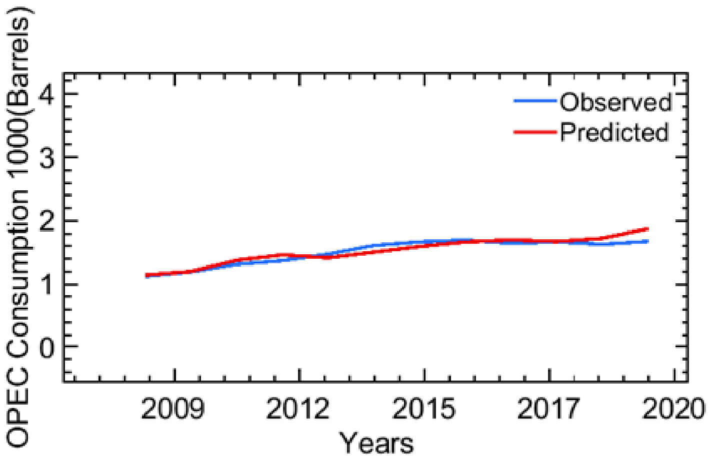

Fig. 5. Testing data prediction results for the optimal RBFNN model.

D. *LSSVM*

The results of the training and testing datasets for the developed LSSVM model for OPEC oil consumption prediction is shown in Table 8 and 9 respectively. It can be observed from the table that three kernel functions were used in the study for the prediction namely, Radial Basis Function, Polynomial Function and Linear Function. The radial basis kernel function was able to calibrate and create the least error margins using the testing data, as shown in the Table 8 with the observed and predicted testing results for the optimal LSSVM model is shown in Fig. 6.

Table 8. Training result for LSSVM.

Kernel Function Type	**Training**				
	MSE	**VAF**	**R^2**	**MAPE**	**PI**
Radial Basis Function	0.0021	99.94156	0.999416	9.04422	1.99155
Polynomial	0.0021	99.93948	0.999396	13.03972	1.99138
Linear	0.00215	99.64147	0.996415	51.12368	1.97479

Table 9. Testing result for LSSVM.

Kernel Function Type	**Testing**				
	MSE	**VAF**	**R^2**	**MAPE**	**PI**
Radial Basis Function	0.695614	-143.164	0.466928	46.04641	-2.42083
Polynomial	0.0021	99.93948	0.999396	13.03972	1.99138
Linear	0.0013	99.64147	0.996415	51.12368	1.97479

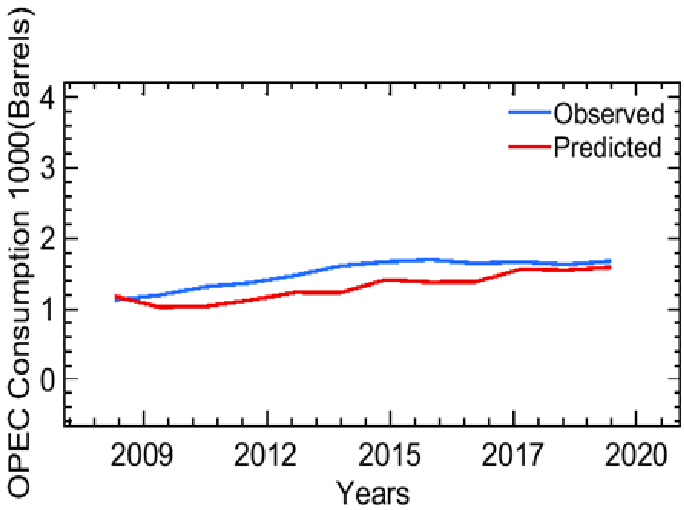

Fig. 6. Testing data prediction results for the optimal LSSVM model.

E. *GMDH*

Table 10 shows the results of the performance indicators for the optimal GMDH model. Table 11 shows the performance indicators for the optimal GMDH model. As shown in the table the MSE, VAF, R^2, MAPE and PI for the BPNN model were 0.002748, 99.24281, 0.992428, 65.6679 and 1.990604 for the training data set and 0.05246, 13.06864, 64.25983, 0.66818, 12.69954 and 65.6679 respectively. The observed and predicted testing results for the optimal GMDH model is shown in Fig. 7The results obtained for both the training and testing data for the GMDH model is shown in Table

Table 10. Training result for GMDH.

Model	Training				
	MSE	VAF	R^2	MAPE	PI
GMDH	0.002748	99.24281	0.992428	65.6679	1.958647

Table 11. Testing result for GMDH.

Model	Testing				
	MSE	VAF	R^2	MAPE	PI
GMDH	0.05246	64.25983	0.66818	12.69954	65.6679

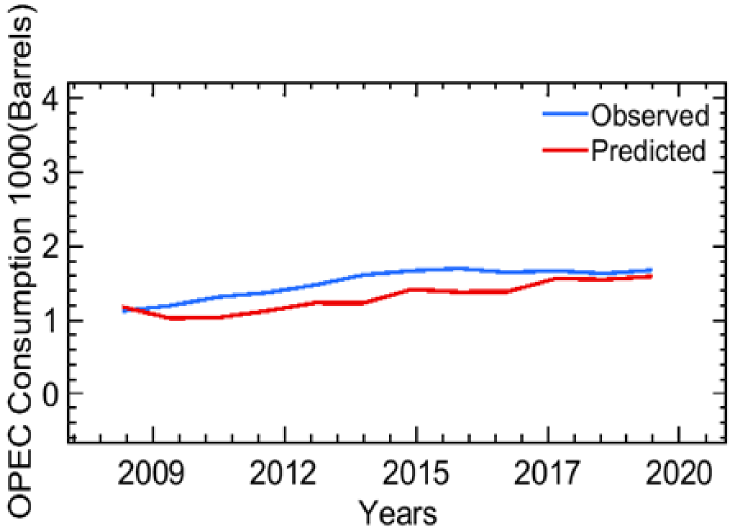

Fig. 7. Testing Data Prediction Results for the Optimal LSSVM Model.

F. *Comparison of Models Test Results*

Table 11 shows the comparative results in terms of MSE, VAF, R^2, MAPE and PI of all the models developed in the study. Based on the results from Table 11, it can be observed that the RBFNN outperformed all the other models with MSE, VAF, R^2, MAPE and PI values of 0.00707, 82.8538, 0.85038, 3.9899.1.532 respectively. In all the models developed the RBFNN recorded the least MSE and MAPE values and the highest VAF and PI values. The RBFNN was followed by GMDH model with MSE, VAF, R^2, MAPE and PI values of 0.05246, 64.2590,0.66818, 12.099, 0.91087. Figure 8 shows the Mean Square Errors and Coefficient of Determination of the developed models. It can be observed that though the coefficient of determination for the LSSVM model was 0.94834, its Mean Square Error was 0.169047. From table 11 it can also be observed that, the VAF, MAPE, PI values of the LSSVM model were 18.69296, 21.9067 and 0.417471. Though the LSSVM model recorded the highest R^2 value in all the models developed, the RBFNNcomparatively outperformed the LSSVM based on the results of the performance matrices used in the study.

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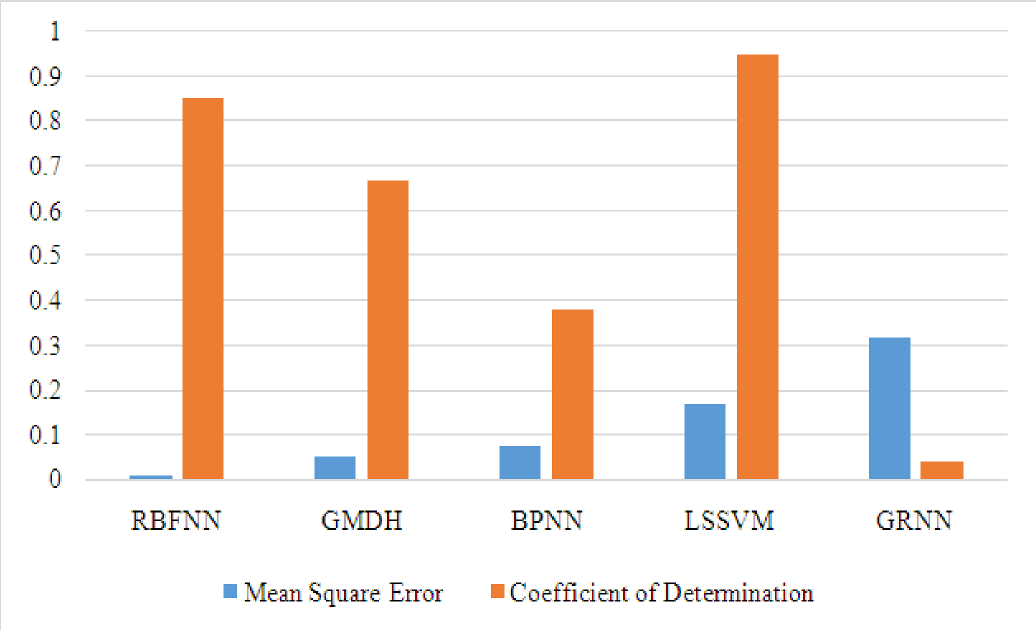

Fig. 8. Mean Square Errors and Coefficient of Determination of the developed AI models.

Table 11. Summary of optimal models test results.

Model	MSE	VAF	R^2	MAPE (%)	PI
RBFNN	0.00707	82.8538	0.85038	3.9899	1.532
GMDH	0.05246	64.2590	0.66818	12.099	0.91087
BPNN	0.07467	13.0686	0.377455	13.3228	0.0310
LSSVM	0.169047	18.69296	0.94834	21.9067	0.417471
GRNN	0.31708	3.24137	0.037512	31.48533	-0.91318

G. *Sensitivity Analysis Results*

Table 12 presents the calculated first order indices for the optimal RBFNN model for OPEC oil based on Sobol's method. The corresponding values in each row indicate the highest first order sensitivity indices in each model.

Table 12. First order indices of input variables.

Model	Input Factors						
	Time	GDP	Values of Import	Crude Oil Production	Population Growth	Oil Prices	Values of Export
RBFNN	0.17494	0.2001	0.00092	0.19	0.0006	0.11617	0.313
GMDH	0.000091	0.000007	0.00005	0.615	0.213	0.0009	0.00001
BPNN	0.00723	0.1722	0.00232	0.5854	0.0014	0.0013	0.01023
LSSVM	0.0253	0.293	0.166	0.0124	0.0123	0.04151	0.0219
GRNN	0.315	0.0995	0.091	0.3111	0.025	0.053	0.0720

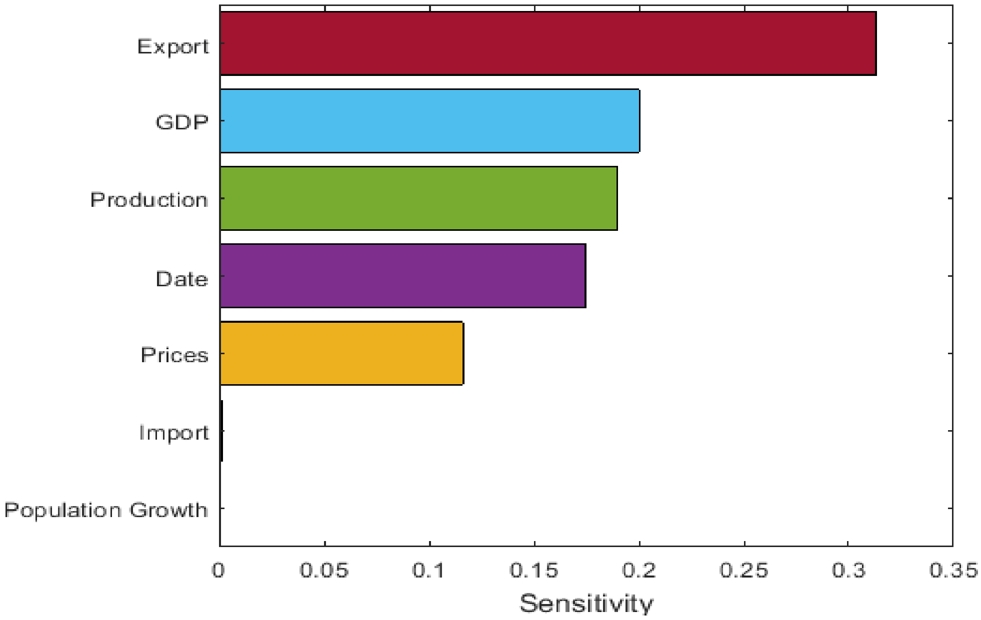

Fig. 9. Sensitivity indices of input variables for the optimal model.

Referring to Table 12, it can be observed that the most the most influential factor that affects oil consumption of the RBFNN model is values of oil export. Based on the interpretation of the sensitivity index, the RBFNN output variation can be reduced by a factor of 0.313 on average by fixing the values of oil export. and the least factor that influence OPEC oil consumption of the RBFNN is Oil Importation and Population Growth. Is shown to be the most influential factor in all the prediction models developed since it recorded the highest sensitivity index whiles Oil production was not most influential factor in the BPNN and the GMDH models developed. The results of the comparative analysis of performance metrics of the developed models shows that GRNN cannot be relied on to satisfactorily predict OPEC oil consumption. Figure 8 shows the sensitivity indices of the input variables of the optimal model.

IV. Conclusion

In this study, five ANN models were developed to predict oil consumption of OPEC using the macroeconomic indicators of OPEC as input variables. Based on the results of the study, the RBFNN model outperformed all the models developed with MSE, VAF, R^2, MAPE and PI of 0.00707, 82.8538, 0.85038, 3.9899 and 1.532 respectively. Results of the sensitivity analysis of the optimal RBFNN showed that the most influential factor that affects oil consumption of OPEC member states is value of Oil Export and the least factor that influence OPEC oil consumption is Oil Importation and Population Growth. OPEC member states can use the findings of this study to design and implement policies in order to prevent global supply and demand imbalances. Further study may consider optimizing the radial basis function neural network with metaheuristic algorithms for oil consumption prediction of OPEC.

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