



Machine Learning Models for Forecasting Petroleum Consumption: A Review

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ABSTRACT

The development and use of intelligent methods as an emerging trend is attracting attention in the academia and industries, including petroleum industry. Forecasting petroleum consumption can go to a greater extent in helping the authority concerned to properly manage petroleum demand and supply, investment analysis, research related to energy as well as the analysis of revenue generation. In this paper, a review of the related literatures for forecasting petroleum consumption has been conducted with the sole aim of establishing a gap for further research. A keyword base search has been performed to find relevant literatures from various academic databases and the papers collected were reviewed to identify their areas of strengths and weaknesses. It has been found that conventional machine learning models are used the most in proposing models for forecasting petroleum consumption while deep machine learning algorithms are used the least.

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INTRODUCTION

Petroleum occurs naturally beneath the earth's surface and can be refined into several products. It is a non-renewable energy source. Petroleum is formed from the decomposition of organic matter – primarily by subjecting zooplankton and algae underneath sedimentary rock to intense heat and pressure. Oil is still considered as the main energy source by the organization of petroleum exporting countries. Chiroma, Khan, Abubakar, Saadi, Hamza, Shuib et al., (2016) refers petroleum as oil. Oil and petroleum have also been used to mean the same by (Li, Wang, Wang, & Li, 2018). Hence, Petroleum and Oil has been used interchangeably in this research work. Oil constituents include liquefied petroleum gases, residual fuel, distillate oil, kerosene, jet fuel, motor gasoline, and other petroleum products (Chiroma, Abdulkareem, Muaz, Abubakar, Sutoyo, Mungad et al., 2015). Oil served as the fuel source for many chemicals, such as fertilizers, drugs, pesticides, plastics, etc. (Anderson, 2017).

Petroleum is among the three types of fossil fuel, and it is widely used in many economic activities, such as construction, industry, residential activities and electricity generation (Abadir & Distaso, 2007). The other types of fossil fuel are natural gas and coal. The term fossil fuel simply means that petroleum has been created by the decomposition of organic matter over millions of years. Although, oil can be consumed directly in rare cases, it has to be refined before use in many other situations. Petroleum consumption increases with economic advancements (Chiroma et al., 2016). Technology and its operations would have not been possible without petroleum as scientific and economic development as well as advancements are directly linked to oil consumption (Wang, Jiang, Zhou, Wu, & Qin, 2016). This simply means that a nation can measure the growth of its economic activities based on the pattern of its petroleum consumption. The recent statistics estimated an increase of oil consumption to 92.3 mobe/d (million barrel of oil equivalent per day) in 2020,

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and further estimated an increase to 97.9 mobe/d and 100.7 mobe/d respectively in 2030 and 2040 (Al-qaness, Abd Elaziz, Ewees, & Cui, 2019). Forecasting OPEC petroleum consumption can go to a greater extent in helping the management of OPEC to properly manage petroleum demand and supply, investment analysis, research related to energy as well as the analysis of revenue generation (Chiroma et al., 2016). By knowing a good estimate of the amount of petroleum a country can consume over a particular period of time, the country can devise an appropriate measure that can reduce the impact of greenhouse effect.

Machine learning has been successfully applied to several areas in petroleum industry. The development and use of machine learning technologies are attracting measurable attention in academia and industries due to their timely response ability and robustness nature for generalization (Evans, 2019). Machine learning techniques demonstrated their potentials in the area of reservoir engineering (Anifowose, Labadin, & Abdulraheem, 2017).

Time taken for oil well placement was found to reduce with neuro-fuzzy algorithm (Zarei, Daliri, & Alizadeh, 2008). Linear regression algorithm was utilized to put 2020 world petroleum production at 4593 (Aydin, 2015). Al-qaness et al., (2019) used a hybrid of the Multi-Verse Optimizer (MVO) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast oil consumption in Korea and Italy, dubbed MVO-ANFIS. Chiroma et al., (2016) used a combination of neural networks and flower pollination algorithms to forecast OPEC oil consumption. Folorunso, Taiwo, and Olabanjo (2018) Proposed Linear Regression (LR) and Random Forest Regression (RFR) to estimate petroleum consumption in Nigeria. To forecast petroleum consumption, (Sujjaviriyasup, 2019) used a hybridized Support Vector Regression (SVR) model with Differential Evolution (DE), (SVR-DE). Ibitoye, Shafiq, and Matrawy (2019) suggested a pipeline leak detection system based on convolutional neural networks. Bi – Long short term memory (Bi-LSTM) network was used to predict Brent oil price (Vo, Nguyen, & Le, 2020). Yu, Zhao, Tang & Yang (2019) used google trend to predict petroleum consumption through the application of big data driven algorithm. These are

just few mentioned areas where machine learning has been successfully applied in oil and gas industry.

METHODOLOGY

Performing a Keyword-Based Search

Various academic databases, such as Google scholar, Elsevier, Scindirect, IEEE xplore, Springerlink, etc., were employed to perform a key-word based searching of papers from 2015 to 2021. The keywords used in this investigation include: Petroleum consumption forecasting/predicting using machine learning, forecasting/predicting petroleum consumption using shallow models, forecasting/predicting petroleum consumption using deep models, forecasting/predicting petroleum consumption using hybrid models, etc. In this investigation, 5 published papers were collected.

Searching Relevant Cited Papers

Papers cited in the references of collected publications that were linked to petroleum consumption forecast were identified as additional papers relevant to the investigation. In this case, 1 more relevant paper was collected.

Reviewing the Papers

All the papers obtained above were reviewed to: identify the Author(s), the name of the machine learning model the Author(s) proposed, state the purpose why the model was proposed, state the function of each component that make up the model, summarize the result obtained after the model's performance was evaluated and state the limitations of the proposed model. In the paper that is being reviewed, if there is any comparative analysis done between the model and other model(s), the result obtained has been briefly stated.

Introducing the Prediction Models

This paper focuses on machine learning models including: traditional machine learning models and deep learning techniques.

MACHINE LEARNING RUDIMENT

Machine learning has united a vast array of algorithms that find their origins in fields ranging from electrical engineering, signal processing,

statistics, financial analysis, genetic sciences, and so on, they also have one more thing in common: the use of computers to automate complex computations. These computations ultimately lead to solving problems that seem so hard that one would believe that they are solved by some intelligent entity (Joshi, 2020). Two categories of machine learning models have been used by different scholars to predict petroleum consumption. These models are: Conventional Learning Model and Deep Learning Model.

Conventional Machine Learning Models for Forecasting Petroleum Consumption

Conventional machine learning models often uses optimization and gradient-descent methods for learning parameterized models. Examples of such models include linear regression, Random Forest Regression, support vector machines, logistic regression, dimensionality reduction, matrix factorization, etc. some of the conventional machine learning models that have been applied to predict petroleum consumption have been discussed in the subsequent section.

Linear Regression (LR) Model

Linear regression is a classic example of linear models. It is also called polynomial fitting and is one of the simplest linear methods in machine learning. The method of linear regression defines the following relationship between input x_i and predicted output \hat{y}_i which is linear as indicated in equation 1.

$$\hat{y}_i = \sum_{j=1}^n x_{ij} \cdot w_j + w_0 \quad (1)$$

\hat{y}_i is the predicted output while the observed output is y_i . $w_i, i = 1, 2, \dots, m$ are called the weight parameters and w_0 is called the bias. Evaluating these parameters is the objective of training. The architecture of LR is shown in figure 1.

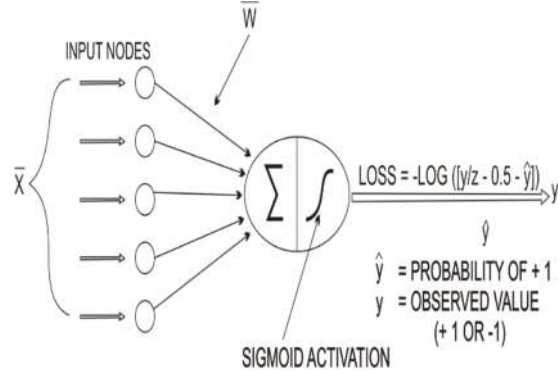


Figure 1: Architecture of Linear Regression

Random Forest Regression (RFR) Model

Bagging (Breiman, 1996) is a variation on Random Forests (Breiman, 2001), but with a layer of unpredictability added on top. Random forests use a different bootstrap sample of the data for each tree and alter the way classification and regression trees are created. The optimum split across all variables is used to split each node in a typical tree. The best predictors from a subset of predictors picked at random are used to split each node in a random forest. This seemingly paradoxical technique outperforms a variety of other classifiers, including discriminant analysis, support vector machines, and neural networks, while also being resistant to overfitting. It's also fairly user-friendly because it just has two parameters (the number of variables in the random subset at each node and the number of trees in the forest) and isn't very sensitive to the settings of those parameters (Liaw & Wiener, 2002). RFR is represented in equation 2.

$$g(x) = f_0(x) + f_1(x) + \dots \quad (2)$$

where the final model g is the sum of simple base models f_i . Here, each base classifier is a simple decision tree, all the base models are constructed independently using a different subsample of the data.

Support Vector Regression (SVR) Model

One of the computational intelligence models is the support vector machine model (Sujjaviriyasup, 2019). It is a supervised learning model used in categorization. In terms of regression analysis, the SVR model is a support

vector machine extension model for regression problems that creates a regression function by using kernel functions to apply a succession of high-dimensional linear and nonlinear functions. In addition, SVR models can be useful for resolving complex problems and determining unknown functional correlations. Equation (3) depicts the SVR model formulation for regression.

$$f(x_i) = \sum_{j=1}^T (\alpha_j - \alpha_j^*) K(x, x_j) + b \quad (3)$$

where α_i and α_j^* are the so-called Lagrange multipliers, b is a scalar threshold, $K(x, x_j)$ is a

kernel function. The kernel functions are the most used for SVR models, which are defined as follows:

$$\text{Linear: } K(x, x_j) = x^T x_j, \quad (4)$$

$$\text{Polynomial: } K(x, x_j) = (\gamma x^T x_j + r)^p, \quad (5)$$

$$\text{Radial basis: } K(x, x_j) = \exp(-\gamma |x - x_j|^2), \quad (6)$$

$$\text{Sigmoid: } K(x, x_j) = \tanh(\gamma x^T x_j + r) \quad (7)$$

Where γ , p and r are kernel parameters.

The basic architecture of SVM is shown in figure 2:

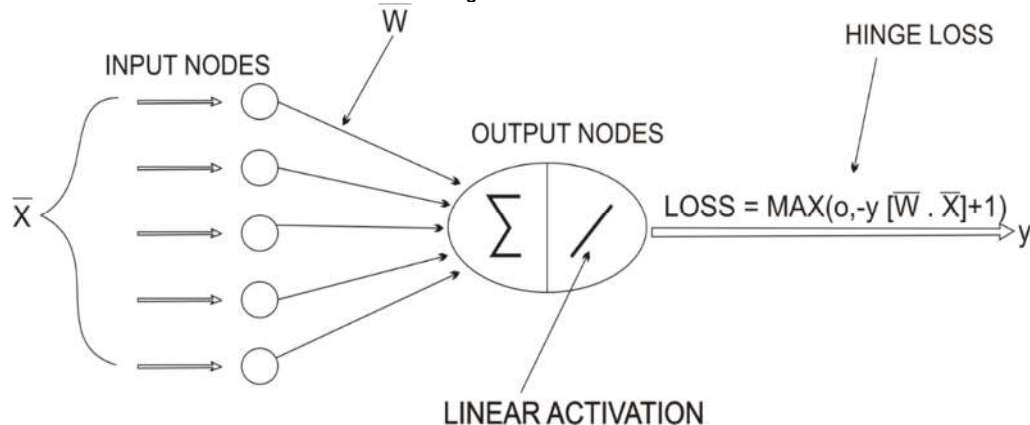


Figure 2: Architecture of Support Vector Regression

Deep Learning Models for Forecasting Petroleum Consumption

A machine learning algorithm is deep if the number of hidden/computational layers are three and above. Sections 3.2.1 and 3.2.2 discuss the deep learning algorithms applied in forecasting petroleum consumption.

Artificial Neural Network (ANN)

The term ANN refers to the machine learning approach that mimic the learning process of the human brain (Aggarwal, 2018). The

components of ANN include the input layer, hidden layer, output layer, neurons and their connection edges referred to as the weights. Each neuron in a current layer is connected to all the neurons in the previous layer. Connections are not allowed among neurons of the same layer. Shallow Neural Networks often contain one or two computational layers; the additional intermediate layer(s) are referred to as hidden layers because their operations are not visible to the users. Figure 3 shows the basic architecture of shallow ANN.

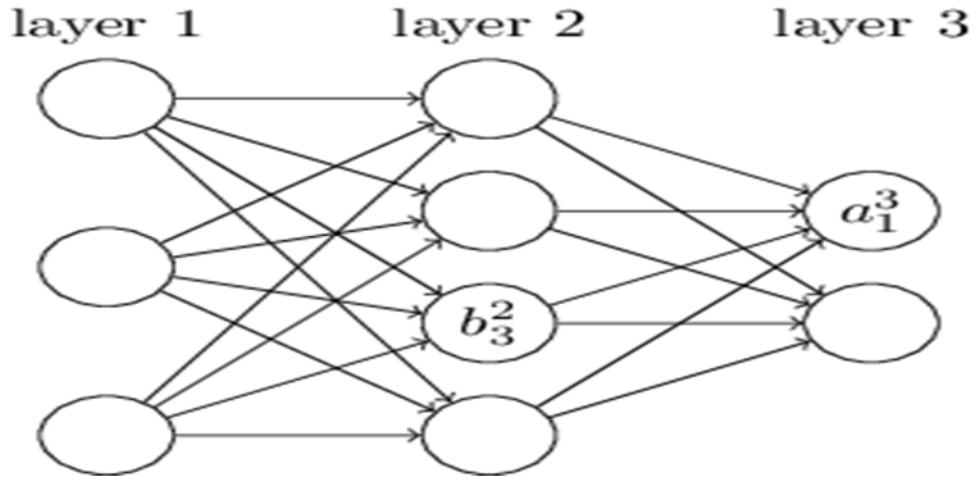


Figure 3: Architecture of an ANN

Neural networks define the following relationships between inputs a_k^{l-1} and output a_j^l :

$$a_j^l = \sigma(\sum_k w_{jk}^l a_k^{l-1} + b_j^l) \quad (8)$$

Where a_j^l is the j^{th} activation of l^{th} layer, σ is a sigmoid function, \sum_k is the sum over all activations k in the $(l-1)^{\text{th}}$ layer, w_{jk}^l is a weight from k^{th} activation of $(l-1)^{\text{th}}$ layer to j^{th} activation of l^{th} layer, a_k^{l-1} is the k^{th} activation of $(l-1)^{\text{th}}$ layer and b_j^l is the bias of the j^{th} activation in l^{th} layer. The sigmoid function is given in equation (9).

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (9)$$

Where $z = \sum_k w_{jk}^l a_k^{l-1} + b_j^l$, is called the weighted sum.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Traditional neural networks (NN) are combined with fuzzy logic in the Adaptive Neuro-Fuzzy Inference System (ANFIS) model. Using fuzzy IF-THEN rules, this model also generates a nonlinear map between the input and output. Figure 1 depicts the basic ANFIS model, which has two inputs (A and B) and an output (O).

The ANFIS model is divided into five layers, each with its own function. The first layer

takes the A and B and uses the generalized Gaussian membership functions (μ) to compute the output of each node (O_{1i}) as shown in equation (10).

$$O_{1i} = \mu_{A_i}(A), i = 1, 2, O_{1i} = \mu_{B_{i-2}}(B), i = 3, 4 \quad (10)$$

$$\mu(A) = e^{-\frac{(x-\rho_i)^2}{\alpha_i}} \quad (11)$$

The two parameters ρ_i and α_i in equation (11) are the set of premise parameters. The membership values of μ are A_i and B_i . The output of each node in the second layer (the firing strength of a rule) is computed next in ANFIS using equation (12).

$$O_{2i} = \mu_{A_i}(A) \times \mu_{B_{i-2}}(B) \quad (12)$$

Thereafter, the node in the third layer (normalized firing strength) computes its output using equation (13).

$$O_{3i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^2 w_i} \quad (13)$$

The adaptive nodes in the fourth layer compute their output depending on the O_{3i} as shown in equation (14)

$$O_{4,i} = \bar{w}_{f_i} = \bar{w}_i(p_i A + q_i y + r_i) \quad (14)$$

In Equation (14), the parameters r_i , q_i , and p_i are the consequent parameters of the i^{th} node. The output of the ANFIS out is calculated as shown in equation (15).

$$Out = \sum_i \bar{w}_i f_i \quad (15)$$

Figure 4 shows the basic architecture of ANFIS.

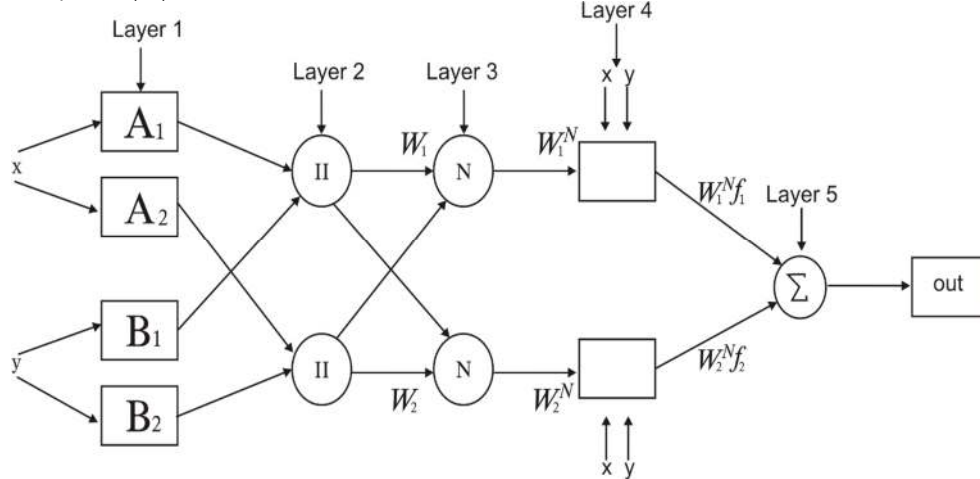


Figure 4: Architecture of an ANFIS

REVIEW OF MACHINE LEARNING MODELS USED TO PREDICT PETROLEUM CONSUMPTION

Al-qaness et al., (2019) hybridized Multi-Verse Optimizer (MVO) algorithm and Adaptive Neuro-Fuzzy Inference System (ANFIS) model (MVO-ANFIS) to forecast oil consumption in Korea and Italy. MVO was employed to optimize ANFIS parameters to improve its prediction performance. ANFIS made the prediction. However, the computational cost of an ANFIS model is high due to complex structure and gradient learning.

Sujjaviriyasup (2019) hybridized Support Vector Regression (SVR) model and Differential Evolution (DE) algorithm (SVR-DE) to forecast petroleum consumption. DE algorithm was used to search for optimal parameters of SVR model, which in turn models the predictive function. However, the false neighbors that existed in reconstructed state space affects the forecasting performance of SVR.

Folorunso et al., (2018) Proposed Random Forest Regression (RFR) model to forecast petroleum consumption in Nigeria. RFR was trained to predict the annual petroleum consumption in Nigeria. RFR models a real valued target, hence the term regression. However, the prediction accuracy of the proposed model can be

improved if the parameters of the machine learning model were tuned.

Folorunso et al., (2018) Proposed Linear Regression (LR) model to forecast petroleum consumption in Nigeria. LR was trained to predict the annual petroleum consumption in Nigeria. LR models a real valued target, hence the term regression. However, the prediction accuracy of the proposed model can be improved if the parameters of the machine learning model were tuned.

Li et al., (2018) proposed the hybridization of Genetic Algorithm (GA) with Grey Neural Network (GNN) (GA-GNN (1, n)) to forecast oil consumption in China. GA optimizes the parameters of GNN, which then predict China's annual oil consumption. However, it is difficult to distinguish the performance of GA-GNN (1, n) and Exponential Smoothing, one of its evaluation algorithms. GA-GNN (1, n) demonstrate better performance in terms of the MSE values, Exponential Smoothing performs more efficiently than GA-GNN (1, n) in terms of MAPE.

Chiroma et al., (2016) hybridized Flower Pollination Algorithm (FPA) and Neural Network (NN) (FPNN) to forecast OPEC petroleum consumption. The FPA was used to train the NN



which predicts OPEC petroleum consumption. However, Neural Network is inherently designed for multi-dimensional data whose attributes are largely independent on one another

Chiroma et al., (2015) hybridizes Artificial Bee Colony (ABC) Algorithm and Levenberg-Marquardt Neural Network (LMNN) (ABC-LM) to model oil consumption in the Middle East Countries involving Jordan, Lebanon, Oman and Saudi Arabia. ABC algorithm was used to optimize the parameters of Levenberg-Marquardt (LM) Neural Network (NN). LM makes the prediction of oil consumption. However, the convergence speed of the proposed model can still be improved with cross entropy cost function.



Table 1: Summary of the Review of Related Works

S/N	Reference	Title	Model Used	Purpose	Dataset	Metrics	Evaluation Algorithms	Results	Limitations
1	(Al-qaness et al., 2019)	A Modified Adaptive Neuro-Fuzzy Inference System Using Multi-Verse Optimizer Algorithm for Oil Consumption Forecasting	MVO-ANFIS	Forecasting monthly oil consumption in Korea and Italy	Official website of U.S Energy Information Administration.	MAE, RMSE, RMSRE, MAP	ANFIS, PSO-ANFIS, GA-ANFIS, WOA-ANFIS and SCA-ANFIS	MVO-ANFIS outperformed ANFIS, PSO-ANFIS, GA-ANFIS, WOA-ANFIS and SCA-ANFIS	Computational cost of an ANFIS model is high due to its complex structure
2	(Sujjaviyiasup, 2019)	Forecasting petroleum consumption using hybrid SVR-DE model emphasizing on optimal parameter selection technique	SVR-DE	Forecasting yearly Petroleum Consumption in Asia & Oceanic, Europe, North America, Africa, Central & South America, Eurasia and Middle East	Official website of U.S Energy Information Administration	MAE, MAPE, Smape	ARIMA and SVR	SVR-DE performed better than ARIMA and SVR	The false neighbors that existed in reconstructed state space affects the forecasting performance of SVR
3	(Folorunso et al., 2018)	A predictive model for estimating petroleum consumption Using machine learning approach	RFR	Predicting yearly Petroleum consumption in Nigeria	Official website of Nigeria Open Data for Africa.	RMSE, MAE, MAPE, R ²	ARIMA	RFR outperformed ARIMA	The prediction accuracy of the proposed model can be improved if the parameters of the machine learning model were tuned
4	(Folorunso et al., 2018)	A predictive model for estimating petroleum consumption Using machine	LR	Predicting yearly Petroleum consumption in Nigeria	Official website of Nigeria Open Data for Africa.	RMSE, MAE, MAPE, R ²	RFR and ARIMA	LR was found to perform better than RFR and ARIMA	The prediction accuracy of the proposed model can be improved if the parameters of the machine



		learning approach							learning model were tuned
5	(Li, et al., 2018)	Analysis and forecasting of the oil consumption in China based on combination models optimized by artificial intelligence algorithms	GA-GNN (1, n)	Forecasting yearly oil consumption in China	China Statistical Yearbook	MAE, MSE, MAPE, SSE	GNN (1, n), ES, Regression and several other combination models	GA-GNN (1, n) performed better than GNN (1, n), Regression and several other combination models	It is difficult to distinguish the performance of GA-GNN (1, n) and Exponential Smoothing (ES)
6	(Chiroma et al., 2016)	A new approach for forecasting OPEC petroleum consumption based on neural network train by using flower pollination algorithm	FPNN	Forecasting OPEC yearly petroleum consumption	EIA of the US Department of Energy official website	MSE, Convergence time	ABCNN, GANN, APSONN and BPNN	The proposed FPNN outperformed ABCNN, GANN, APSONN and BPNN in terms of forecasting accuracy, convergence time and robustness	NN is inherently designed for multidimensional data in which the attributes are largely independent on one another
7	(Chiroma et al., 2015)	An Intelligent Modeling of Oil Consumption	ABC-LMNN	Modelling yearly oil consumption in Middle East Countries involving Jordan, Lebanon, Oman and Saudi Arabia	EIA of the US Department of Energy official website	MSE	BPNN, LMNN and GA-NN	ABC-LM outperformed BPNN, LMNN and GA-NN	NN is inherently designed for multidimensional data in which the attributes are largely independent on one another



METHODS OF DATA COLLECTION

Data can be collected or gathered in order to be used in the actual implementation of the proposed model. Data can be obtained either by simulation or real world scenario. Simulation involves the collection of data using specialized software or tools that mimic real world instances.

An example of simulation tool is OMNet++. A real world scenario involves the use of actual petroleum consumption data available. All the papers reviewed in this work collected data through the real world scenario. Table 2 shows the methods of data collection used by the reviewed papers.

Table 2: Data Collection Methods Used by the Reviewed Papers

Reference	Data Collection Methods
(Al-qaness et al., 2019)	The actual consumption data is obtained from the Official website (http://www.eia.gov/) of U.S Energy Information Administration which is freely available online.
(Sujjaviyiasup, 2019)	The actual consumption data is obtained from the Official website (http://www.eia.gov/) of U.S Energy Information Administration which is freely available online.
(Folorunso et al., 2018)	The actual consumption data is obtained from the Official website (https://nigeria.opendataforafrica.org/) of Nigeria Open Data for Africa which is freely available online.
(Folorunso et al., 2018)	The actual consumption data is obtained from the Official website (https://nigeria.opendataforafrica.org/) of Nigeria Open Data for Africa which is freely available online
(Li, et al., 2018)	China Statistical Yearbook
(Chiroma et al., 2016)	The actual consumption data is obtained from the Official website (http://www.eia.gov/) of U.S Energy Information Administration which is freely available online.
(Chiroma et al., 2015)	The actual consumption data is obtained from the Official website (http://www.eia.gov/) of U.S Energy Information Administration which is freely available online.

Overview of Forecasting Models

It can be observed from Table 3 that the proportion of conventional machine learning models, shallow models and deep models are 28.6%, 57.1% and 14.3% respectively. It can be concluded that shallow models are applied the most in petroleum consumption prediction. Most of the models focused on the long-term petroleum consumption forecasting, followed by the medium-term forecasting and none considers short-term forecasting. The proportion of the models for yearly (long-term), monthly (medium-term) and daily (short-term) petroleum consumption forecasting are 85.7%, 14.3% and 0%

respectively. Regarding the application area, 14.3% model applied to forecast petroleum consumption of regions, 14.3% model applied to forecast petroleum consumption of OPEC countries and 71.4% models applied to forecast petroleum consumption at national level. Based on this, it can be concluded that forecasting petroleum consumption plays an important role in the development of a country and raises a great interest of the researchers in this field. According to the findings of this research, none of the machine learning models was applied to forecast petroleum consumption in the world.

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Table 3: Models Used to Forecast Petroleum Consumption

Models	Type	Forecasting Horizon (FH)	Application Area (AA)	Number by Type			Number by Forecasting Horizon (FH)			Number by Application Area (AA)		
				Type	Number	Proportion (%)	Forecasting Horizon (FH)	Number	Prop. (%)	Application Area (AA)	Number	Proportion (%)
Linear Regression (LR)	Conventional	Yearly	National	Conventional	2	28.6	Yearly	6	85.7	National	5	71.4
Random Forest Regression (RFR)	Conventional	Yearly	National									
Support Vector Regression (SVR)	Shallow	Yearly	Region									
Neural Network (NN)	Shallow	Yearly	OPEC	Shallow	4	57.1				Region	1	14.3
Levenberg-Marquardt Neural Network (LMNN)	Shallow	Yearly	National									
Grey Neural Network (GNN)	Shallow	Yearly	National									
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Deep	Monthly	National	Deep	1	14.3	Monthly	1	14.3	OPEC	1	14.3

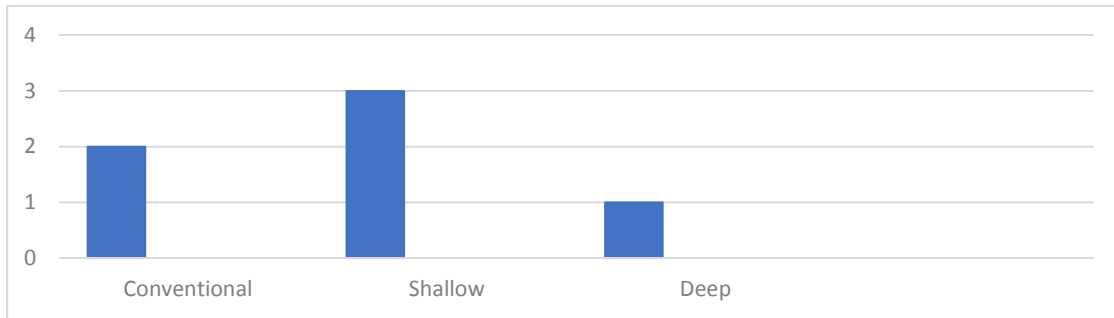


Figure 5: Bar Chart Showing Machine Learning Models Used to Forecast Petroleum Consumption

Figure 5 shows that shallow machine learning models were used the most in forecasting petroleum consumption, followed by conventional

models. Deep models are applied the least in forecasting petroleum consumption.

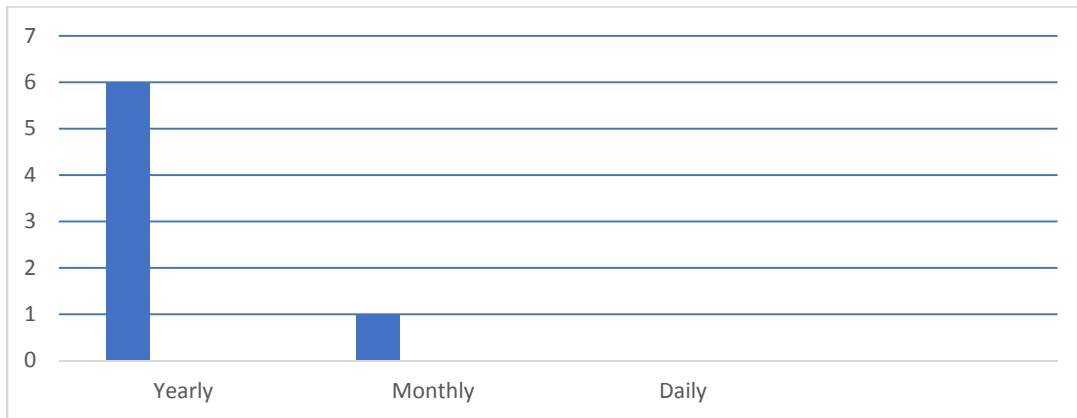


Figure 6: Bar Chart Showing Petroleum Consumption Prediction by Horizon

Figure 6 shows that machine learning models were mostly used for forecasting yearly petroleum consumption. Few of the models were

used to forecast monthly petroleum consumption, while none was used to forecast daily petroleum consumption.

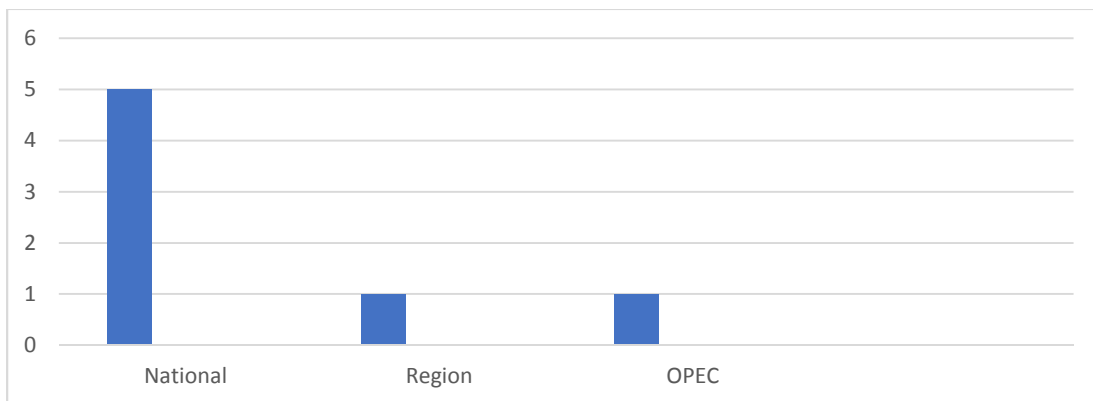


Figure 7: Bar Chart Showing Petroleum Consumption Prediction by Application Area.



Figure 7 shows that machine learning models were mostly applied to forecast petroleum consumption at national level. Few of the models were used to forecast petroleum consumption both at regions and OPEC.

DISCUSSION

Table 3 shows that the proportion of Conventional machine learning models, shallow models and deep models used in forecasting petroleum consumption are 28.6%, 57.1%, and 14.3% respectively. All the Conventional models as well as the shallow models were used for forecasting yearly petroleum consumption. The deep model was used to forecast monthly

petroleum consumption. Machine learning models were used the most in predicting petroleum consumption at national level. According to the findings of this research work, none of the machine learning models was used in predicting global petroleum consumption.

Academic Databases

The papers that applied machine learning in the prediction of petroleum consumption were found to be available and obtained from five different academic databases. These academic databases and the corresponding number of papers are shown in table 4.

Table 4: Academic Databases and Corresponding Number of Papers

Academic Database	Number of Papers
Elsevier	2
Springer	1
LAUTECH	1
Electronics	1
Songklanakarin J. Sci. Technol	1

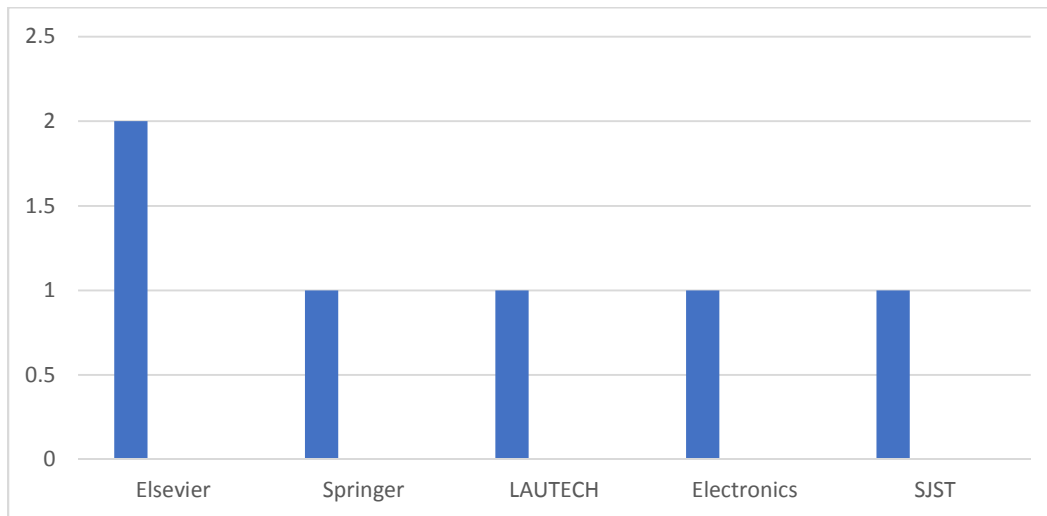


Figure 8: Bar Chart Showing Academic Databases and Corresponding Number of Papers

Figure 8 shows that two of the papers reviewed were obtained from the Elsevier academic database and one paper each obtained from Springer, LAUTECH, Electronics and SJST academic databases.

Publication Trends

The trends of publications over the period of six years as describe in table 5, indicate that there is an increase in the publication trends.



Table 5: Publication Trends

Year	Papers
2015	1
2016	1
2018	2
2019	2

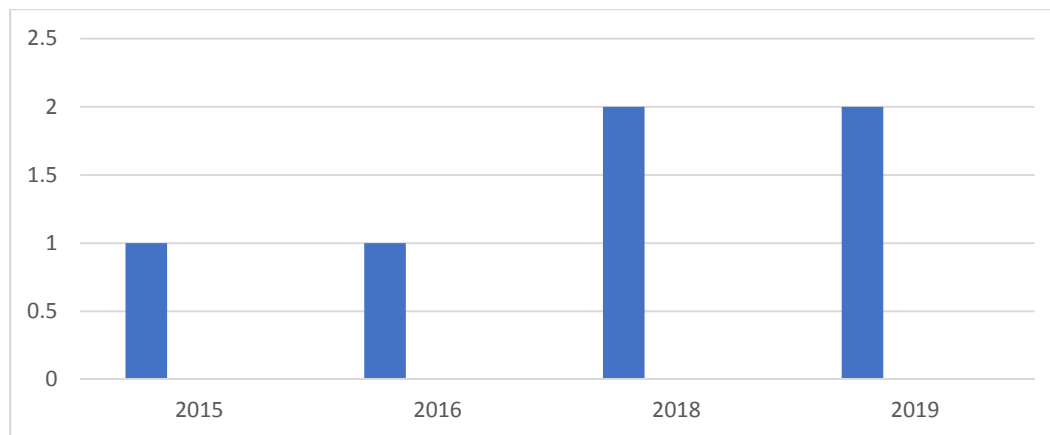


Figure 9: Bar Chart Showing Publication Trends

Figure 9 shows that one relevant literature is obtained each in 2015 and 2016. It has also shown that two relevant literatures were obtained each in 2018 and 2019.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Suggestions for future research are concluded as follows: first, there is a need for the application of deep learning models in long-term and short-term petroleum consumption forecasting, because according to the findings of this work none of such models was used to make the prediction of long-term or short-term petroleum consumption. (Chiroma et al., 2016) recommended that cuckoo search algorithm or flower pollination algorithm be hybridized with Recurrent Neural Network (RNN) to forecast petroleum consumption. But RNN has certain limitations such as failure to analyze series of data with different trends and seasonality as a result of exploding, vanishing gradient as well as oscillating weights (Aggarwal, 2018). RNN is also inherently endowed with poor long-term memory (Aggarwal, 2018). An RNN variant, Long Short-Term Memory (LSTM) can do well to handle the limitations of

RNN such as poor long-term memory (Aggarwal, 2018) and failure to analyze series of data with different trends and seasonality as a result of exploding, vanishing gradient as well as oscillating weights (Aggarwal, 2018).

REFERENCES

- Abadir, K. M., & Distaso, W. (2007). Testing joint hypotheses when one of the alternatives is one-sided. *Journal of Econometrics*, 140(2), 695-718.
- Aggarwal, C. C. (2018). Neural networks and deep learning. *Springer*, 10, 978-973.
- Al-qaness, M. A., Abd Elaziz, M., Ewees, A. A., & Cui, X. (2019). A modified adaptive neuro-fuzzy inference system using multi-verse optimizer algorithm for oil consumption forecasting. *Electronics*, 8(10), 1071.
- Anderson, R. N. (2017). 'Petroleum Analytics Learning Machine' for optimizing the Internet of Things of today's digital oil field-to-refinery petroleum system. Paper presented at the 2017 IEEE International Conference on Big Data (Big Data).



- Anifowose, F. A., Labadin, J., & Abdurraheem, A. (2017). Ensemble machine learning: An untapped modeling paradigm for petroleum reservoir characterization. *Journal of Petroleum Science and Engineering*, 151, 480-487.
- Aydin, G. (2015). Regression models for forecasting global oil production. *Petroleum Science and Technology*, 33(21-22), 1822-1828.
- Breiman, L. (1996). Bagging predictors. *Machine learning*, 24(2), 123-140
- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.
- Chiroma, H., Abdulkareem, S., Muaz, S. A., Abubakar, A. I., Sutoyo, E., Mungad, M., . . . Herawan, T. (2015). An intelligent modeling of oil consumption *Advances in Intelligent Informatics* (pp. 557-568): Springer.
- Chiroma, H., Khan, A., Abubakar, A. I., Saadi, Y., Hamza, M. F., Shuib, L., . . . Herawan, T. (2016). A new approach for forecasting OPEC petroleum consumption based on neural network train by using flower pollination algorithm. *Applied Soft Computing*, 48, 50-58.
- Evans, S. J. (2019). *How digital engineering and cross-industry knowledge transfer is reducing project execution risks in oil and gas*. Paper presented at the Offshore Technology Conference.
- Folorunso, S., Taiwo, A., & Olabanjo, O. (2018). A predictive model for estimating petroleum consumption using machine learning approach. *Lautech journal of engineering and technology*, 12(2), 80-87.
- Ibitoye, O., Shafiq, O., & Matrawy, A. A Convolutional Neural Network Based Solution for Pipeline Leak Detection.
- Joshi, A. V. (2020). *Machine learning and artificial intelligence*: Springer.
- Li, J., Wang, R., Wang, J., & Li, Y. (2018). Analysis and forecasting of the oil consumption in China based on combination models optimized by artificial intelligence algorithms. *Energy*, 144, 243-264.
- Sujjaviriyasup, T. (2019). Forecasting petroleum consumption using hybrid SVR-DE model emphasizing on optimal parameter selection technique. *Songklanakarin Journal of Science & Technology*, 41(6).
- Vo, A. H., Nguyen, T., & Le, T. (2020). Brent Oil Price Prediction Using Bi-LSTM Network. *Intelligent automation and soft computing*, 26(6), 1307-1317.
- Wang, J., Jiang, H., Zhou, Q., Wu, J., & Qin, S. (2016). China's natural gas production and consumption analysis based on the multicycle Hubbert model and rolling Grey model. *Renewable and Sustainable Energy Reviews*, 53, 1149-1167.
- Zarei, F., Daliri, A., & Alizadeh, N. (2008). *The use of neuro-fuzzy proxy in well placement optimization*. Paper presented at the Intelligent Energy Conference and Exhibition.