Petroleum and Coal

Article Open Access

Modelling Annual Natural Gas Demand Forecasting Using Non-Linear Autoregressive with Exogenous Input (NARX) Neural Networks

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Received November 11, 2024; Accepted March 16, 2025

Abstract

Lack of reliable forecasting models hinders informed decision making, leading to inefficiencies, price fluctuations, and potential energy shortages. This challenge is compounded by the complex interplay of factors like populations growth and fluctuating natural gas prices, which traditional models struggle to capture. This study using statistical performance metrics that includes MSE, RMSE, MAE and R^2 analyzed the performance of three NARX models with 1,2, and 3 time delays that integrates factors such as populations, GDP per capita, natural gas price, natural gas reserves and historical data, in predicting average annual natural gas demand in Nigeria. Trained with the Levenberg –Marquardt algorithm in MATLAB, the impact of varying the network time delay and hidden neurons on the NARX models performance was investigated. Obtained results show that increasing the network time delay diminishes the NARX model performance and NARX-1 with average MSE and R^2 values of 0.003 and 0.99123 for training, validation, testing and MSE and R^2 values of 0.0003 and 0.99879 respectively for training was identified as the optimal model configuration with a superior prediction ability having 1 network delay and 20 hidden neurons. The obtained results show the predicted long term projection value of average natural gas demand for 10 years (2024 to 2033) to fall between (12 to 18) bcm. It is then concluded that the average natural gas demand for Nigeria is expected to continue rising as population and GDP per capita increases and the natural gas price reduces, and that the enhanced prediction accuracy of the NARX model can significantly contribute to more technical decision making by concerned majors and policy makers due to the pivotal role that energy demand planning holds in country's development.

Keywords: *NARX; Forecasting; Time-delay; Neural networks; Natural gas demand.*

1. Introduction

Natural gas is widely regarded as a cleaner alternative to other fossil fuels, such as crude oil and coal due to its lower carbon footprint when used for energy generation. In the current era of decarbonization and sustainability, natural gas is poised to maintain its dominant position as an energy source, playing a crucial role in transitioning from fossil fuels to renewable energies. Its potential to stimulate economic development and provide substantial employment opportunities underscores its importance in enhancing living standards.

The energy shortage in Nigeria has been a longstanding concern for both the government and populace [1]. Various interventions at the community, state, and national levels have had limited impact on addressing the energy challenges [2]. Studies [3-5] have shown that the various effort by government in developing the energy mix to curtain the energy shortage has yielded less success, though the gas sub-sector was identified as been critical and capable of driving the nation's economic development. Ubani and Onyejekwe [6] in their study on environmental impact of gas flaring in the Niger Delta region of Nigeria stated that the nations hydrocarbon reserves feature more gas than crude oil, making it essential to grasp how its demand will change to support rapid economic growth [7].The projected global increase in demand for natural gas is driven by the growing need for cleaner energy adoption worldwide, emphasizing its vital role in the social and economic progress of nations embracing sustainable energy trends. This growing significance highlights an intriguing studies by researchers [8-10] in developing quantitative energy demand forecasting models for natural gas within the energy sectors due to the government strict energy production regulations and growing environmental concerns. Forecasting natural gas demand holds immense importance in Nigeria energy policies and planning, as inaccurate estimation of natural gas consumption can have significant economic repercussions for end consumers and mismanagement of supplies and infrastructure [11]. Moreover, the nexus between natural gas consumption and economic growth is non-linear, emphasizing the importance of accurate estimations to ensure sustainable economic development [12].

A reliable and consistent energy supply is crucial for a nation's economic and societal advancement, in furtherance to this, Liu *et al.* [13] in their study on forecast of natural gas consumption in Jiangsu province based on combination factors concluded that policy makers must understand the projected energy demand for effective plan of future energy supply. Natural gas demand forecasting is crucial aspect of energy planning, particularly in an industry marked by risks and uncertainties. It involves utilizing models to analyze historical data and offer insights into future energy demand trend [14]. The time series approach can be used in accomplishing natural gas demand forecasting [15]. The importance of data on natural gas demand forecasting has been investigated by researchers [9,16] in their respective studies and it was generally agreed that having accurate energy demand data is key to both government bodies and midstream companies in planning future capacity development and investments within the natural gas sector. The energy crisis of the 1970s serves as a prime example of having accurate energy data.

Study [17] on forecasting natural gas demand methods reveals analytical or physical method that relies heavenly on variable that influences natural gas consumption such as weather related parameters, economic factors and demographic factors as a method. This method leverages on mathematical equations to model interactions between input parameters and demand [18]. However, precise demand forecasting is a difficult task due to the inherent non-linear nature of natural gas demand as a time series problem, therefore, analytical modeling is becoming increasingly challenging [19]. This complexity has triggered researches [20-23] in the development of new techniques such as statistical, artificial intelligence as well as hybrid approaches, which has effectively helped in estimating the non-linear input-output correlations in time sequence data [24].

This study employs a non-linear autoregressive with exogenous input (NARX) neural network model in modeling natural gas demand forecasting, utilizing a multivariate approach that incorporates input variables such as population, GDP per capita, average natural gas price, and gas reserves, with data specific to Nigeria.

2. Materials and method

2.1. Materials

First, comprehensive lists of all the materials and corresponding procedures used for this study were defined accordingly. These includes time series dataset that spans from the year 1975 to 2023 that encompasses input data variables such as average annual population of Nigeria, Nigeria's GDP per capita, the average annual price of natural gas (based on Henry Hub), and Nigeria's natural gas reserves with the target output dataset on the average annual natural gas consumption, that was sourced from the Nigeria gas company. Artificial neural network (ANN) model that utilizes the non-linear autoregressive with exogenous input (NARX) time series forecasting technique was carried out using MATLAB R2022b using the Levenberg-Marquardt (LM) algorithm. The MATLAB stands out as a widely used programing and numeric computing software in the field of engineering and science. This material was used in this study for data analysis, model development and model creation in combination with a desktop environment and a programing language that was tailored for matrix and array mathematics. The MATLAB provided the learning capability, engineering classification, regression, clustering and deep learning. The evaluation matrices used in this study are mean absolute error (MAE), mean square error (MSE), the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE).

2.2. Method

2.2.1. NARX model description

The modeling and simulation process involved in this study to achieve the desired objectives is succinctly discussed and summarized through the block diagram represented in Figure 1.

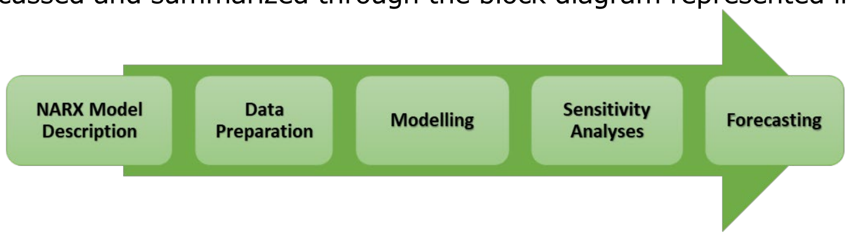

Figure 1. Block diagram of methods.

The NARX (non –linear autoregressive with external input) neural network is a recurrent dynamic neural network extensively employed for time series modeling. This model incorporates an exogenous input that allows it to establish the relationship between the current value of time series, past values of the same series and current past values of external series. The mathematical representation of NARX model is according to equation 1 below.

$$f(t) = f[x(t-1), \dots x(t-d), y(t-1) \dots., y(t-d)] \quad (1)$$

where $f(t), x(t)\ and\ t$ are output parameter, input parameter and discrete time step respectively.

The non-linear correlation between $y(t), x(t)$ is encapsulated by the function f. The NARX model predicts the series $f(t)$ based on the past values of $y(t)$ and another series $x(t)$. The idea behind equation 1 is that the past values of $x(t)$ and $y(t)$ have an impact on the current value of $y(t)$. The hidden layer iterations in this model is accomplished by modifying hidden neurons over successive time delays with inputs linked to network weights. The weight matrices that link the hidden layer's other layers to their respective inputs and biases is determined using the net input function rule with the output of these weight function.

2.2.2. Data sourcing and preparation

The obtained data sourced from the Nigeria gas company used in this study contain key information on average annual population of Nigeria, Nigeria GDP per capita, the average price of natural gas (based on Henry Hub), Nigeria natural gas reserves and annual natural gas demand as it targets output. Consequently, the complete dataset used in this study comprises four input dataset and one target output dataset time series data spanning from the year 1975 to 2023 consisting of 49 data points both for the input dataset and the target output dataset and was used for a long term forecasting for a period of 10 years (2024 to 2033). This raw data was preprocessed for further analysis which is an important step in the data mining process that allows the identifications and corrections of errors within the dataset, along with the removal or adjustment of noisy data. A comprehensive understanding of this dataset, taking into account the interrelationship between the input and target was followed in executing this process.

2.2.3. NARX modeling techniques

For this study, three distinct NARX configurations, named NARX-1, NARX-2, and NARX-3 were examined with their numerical suffix indicating the number of time delays in each configuration. The time delays here play a crucial role in measuring dataset autocorrelation, filtering nonlinear data, and aided the prediction. Sensitivity analysis were then carried out on four separate neuron configuration with the values 5, 10, 15 and 20 respectively. The performance of the NARX models was systematically compared using MSE and R^2 as their performance metrics and the most effective model determined and selected for forecasting by considering both time delays and number of neurons. The NARX network was trained using the Levenberg-Marquardt training algorithm, involving multiple iterations and investigations. The dataset was divided into 70% training, 15% validation, and 15% testing data. The network structure for the NARX model, considering a time delay of 1 and 20 neurons is represented in Figure 2 while the step-ahead predictions is illustrated in Figure 3. Figure 4 illustrate the flowchart for NARX model implementation.

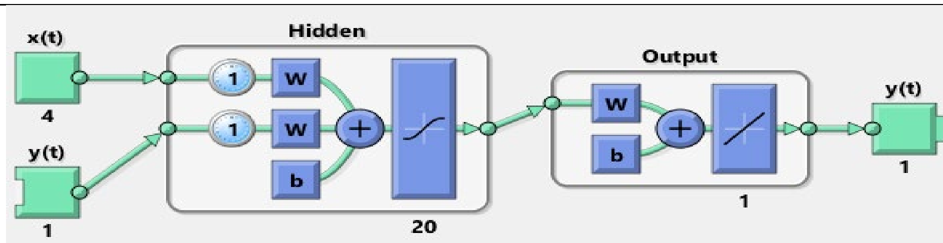

Figure 2. ANN neural network (open loop) for training

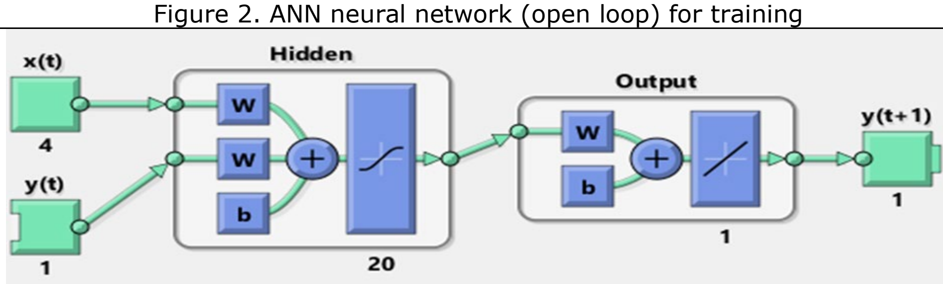

Figure 3. ANN NARX predict one step ahead view

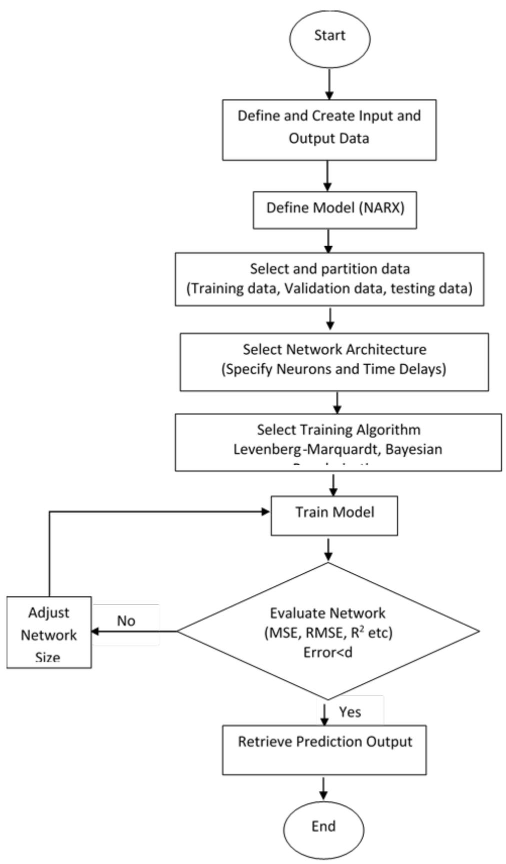

Figure 4. Flowchart for NARX model implementation.

2.2.4. Model selection and evaluation

The model performance was evaluated using mean squared error (MSE) and coefficient of determination according to equations 2 and 3 below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(x_{p,i} - x_{a,i}\right)^2 \qquad (2)$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(x_{a,i} - x_{p,i}\right)^2}{\sum_{i=1}^{n}\left(x_{p,i} - x_{a,ave}\right)^2} \qquad (3)$$

The NARX model with the least MSE value and highest R^2 value is selected and used for predicting the natural gas demand in this study.

3. Results and discussion

3.1. Results

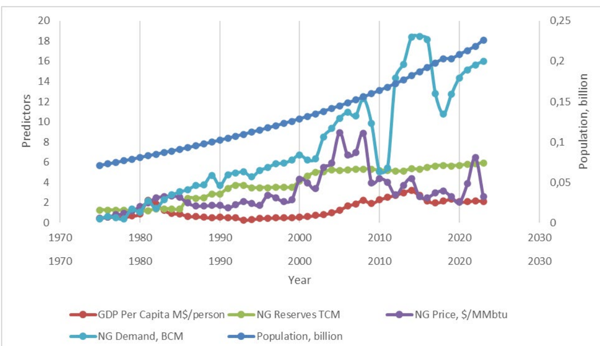

Figure 5. Trend of time series data

The results and discussions on Nigeria's natural gas demand is presented and discussed below. Figure 5 shows the trend of time series data results obtained by plotting both the input and target output variables against the year. Tables 1 to 3 shows the detailed sensitivity analysis results to determine the parametric sensitivity of the modeling in terms of the relationship between the input variable and the target output response for NARX-1, NARX-2 and NARX-3 obtained using 5,10,15, and 20 neurons on each model based on the historical time series data. Figures 6 to 8 indicates the results of the effect of the hidden neurons for each time delay for the NARX model as obtained using Tables 1 to 3.

Figure 1. Analysis of NARX-1 configuration to determine the best hidden neuron.

Hidden neurons	Training		Validation		Testing	
	MSE	R^2	MSE	R^2	MSE	R^2
5	0.01246	0.95645	0.00205	0.98430	0.05489	0.86708
10	0.03551	0.90439	0.02557	0.86814	0.39930	0.97414
15	0.00012	0.99602	0.01098	0.99600	0.06121	0.94387
20	**0.00030**	**0.99879**	**0.00624**	**0.98866**	**0.00443**	**0.98624**

Table 2. Analysis of NARX-2 configuration to determine the best hidden neuron

Hidden neurons	Training		Validation		Testing	
	MSE	R^2	MSE	R^2	MSE	R^2
5	0.01272	0.95707	0.00546	0.96256	0.03637	0.85711
10	0.00867	0.97535	0.01063	0.96176	0.08585	0.90522
15	0.03552	0.91218	0.01640	0.96999	0.06402	0.95897
20	**0.00936**	**0.97063**	**0.01877**	**0.98297**	**0.06082**	**0.95263**

Table 3. Analysis of NARX-3 configuration to determine the best hidden neuron.

Hidden neurons	Training		Validation		Testing	
	MSE	R^2	MSE	R^2	MSE	R^2
5	0.05716	0.86065	0.10037	0.68184	0.01806	0.98133
10	**0.00245**	**0.99776**	**0.05905**	**0.76065**	**0.01373**	**0.97828**
15	0.00032	0.99960	0.12961	0.73309	0.03558	0.85381
20	0.02158	0.97164	0.02063	0.83458	0.19178	0.61553

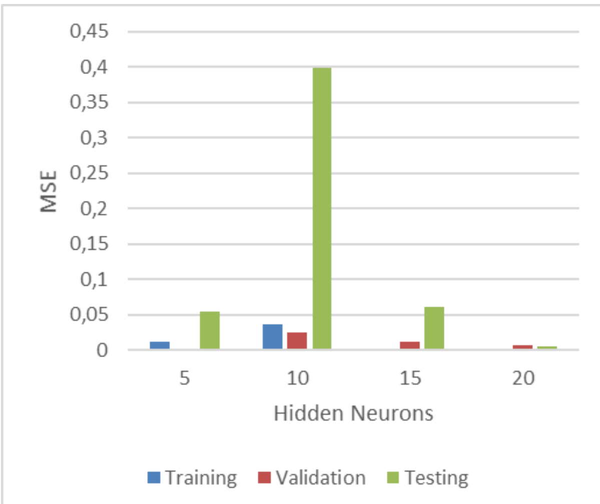

Figure 6. Determination of hidden neuron for NARX-1

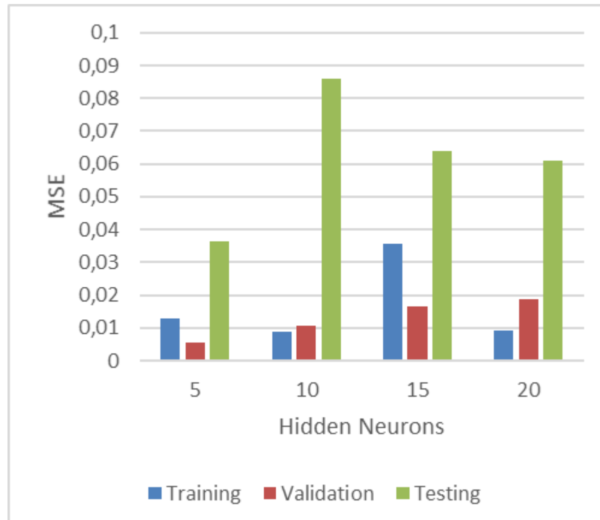

Figure 7. Determination of hidden neuron for NARX-2

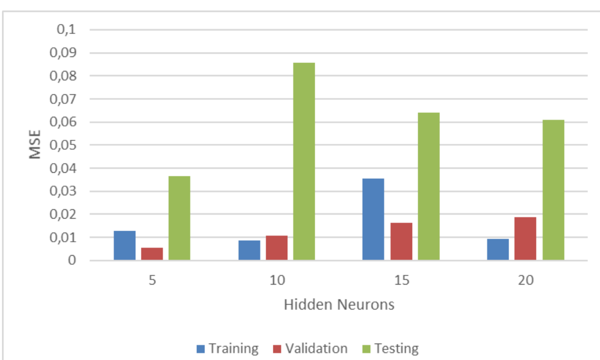

Figure 8. Determination of hidden neurons for NARX-3.

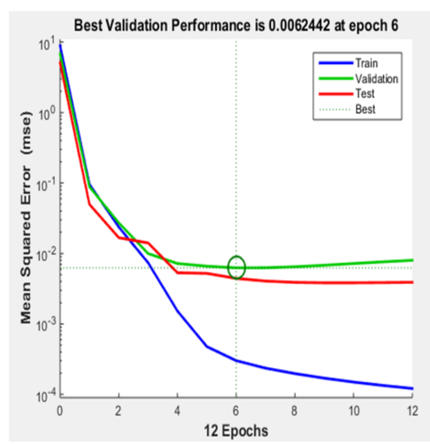

Figure 9. Determination of best validation performance for Narx-1.

The performance evaluation results for NARX-1 involving number of epochs with a series of iterative processes each to determine the optimal performance throughout the training process is represented in Figure 9. The results of the performance of the NARX-1 model in terms of autocorrelation which involves analyzing the lagged values of a time series is presented in Figure 10 while Figure 11 shows the time series plot result that provide detailed insights into the NARX -1 model as functions of output target parameters.

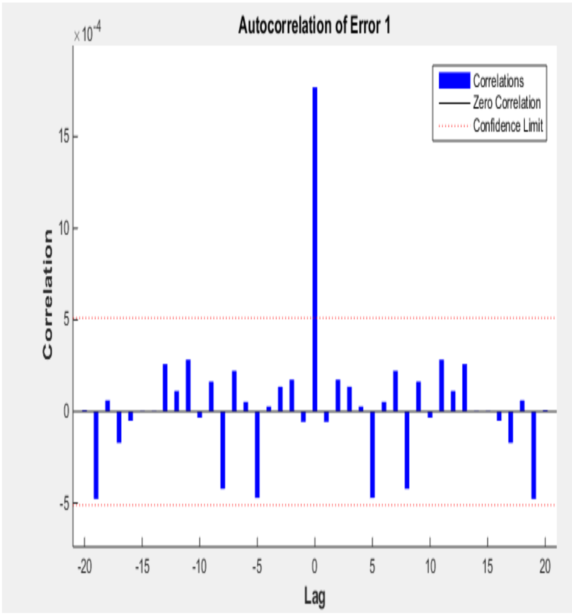

Figure 10. Autocorrelation error for NARX-1

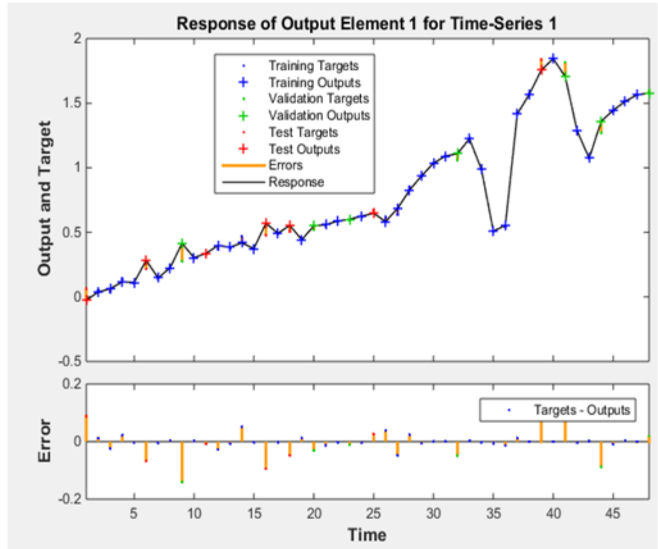

Figure 11. Time series based prediction of average annual natural gas demand for NARX-1.

The regression analysis to establish the pattern trend between the actual data and the predicted target out response is shown in Figure 12 while Table 4 shows the performance metrics for NARX-1. Table 5 shows the predicted future values of the average annual natural gas demand forecast result as obtained using NARX-1 while Figure 13 shows the average annual natural gas demand forecast as obtained from Table 5.

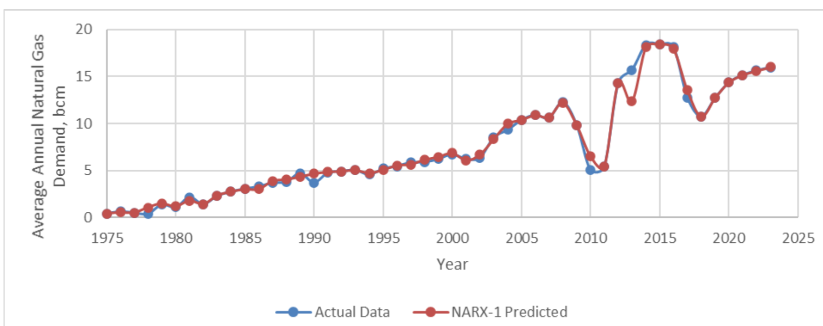

Figure 12. Actual vs predicted average natural gas demand for NARX-1.

Table 4. Performance metrics for NARX-1.

MSE	RMSE	MAE	MAPE	R^2
0.003396	0.058271	0.025333	0.079376	0.988155

Table 5. Forecasted average annual natural gas demand

Year	Forecast, bcm	2029	15.83146
2024	12.58929	2030	16.14099
2025	14.76996	2031	16.56538
2026	16.95775	2032	15.34007
2027	14.0357	2033	17.71746
2028	16.17459		

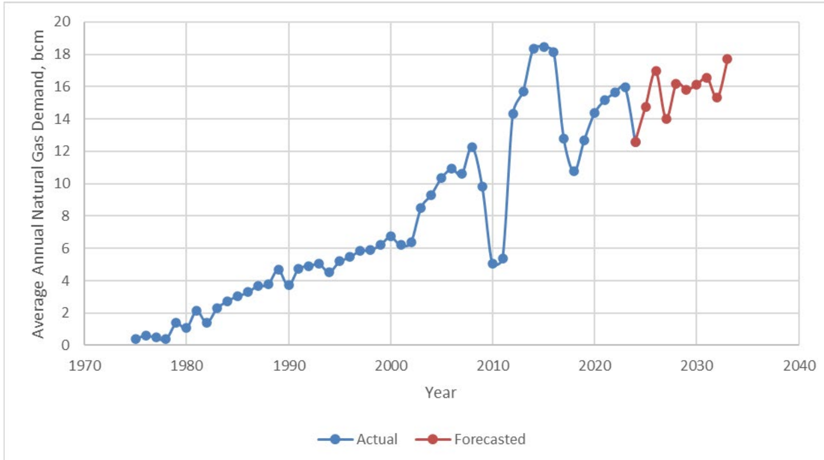

Figure 13. Average annual natural gas demand forecast.

3.2 Result discussion

3.2.1. Time series data trend

The trend of time series data as presented in Figure 5 shows generally that the natural gas demand exhibits a rising pattern with notable declines in the year 2009,2010, 2019, and 2020. The decrease in demand during 2009 and 2010 can be attributed to the global economic recession of 2008, impacting various economies. Similarly, the decline in natural gas demand in 2019 and 2020 is attributed to the COVID-19 pandemic on nations worldwide. Despite these significant downturns, the natural gas demand demonstrates a consistent average demand upward trajectory. The continuous rise from 1975 to 2023 on the population of natural gas from the obtained result is paralleled by an increasing trend in natural gas reserves over the years. The expanding population is identified as a contributing factor to the heightened demand, which is in conformity to the findings of Mustapha *et al.* [25] who established a correlation between energy demand and economic indicators. Additionally, as revealed from the result indicates that the GDP per capita of Nigeria shows fluctuations over time, with distinct phases of growth and decline, ultimately stabilizing at a relatively constant level.

3.2.2. Modeling sensitivity analysis

The result of the detailed analysis carried out to examine time delays and the number of neurons with the aim of determining the parametric sensitivity of the model and understand the relationship between input variable and the target output response are given in Tables 1 through 3 while the effects of the hidden neurons for each time delay are shown in Figure 6 through 8. The statistical analysis of the obtained result from Tables 1 to 3 shows that the optimal number of neurons for the NARX-1 and NARX-2 models configuration is 20 and 10 for NARX-3. This can be explained from their statistical error parameters, which is the performance metrics used in this study. Remember that the closer MSE is to zero, the more accurate the prediction, implying that the regression line is very close to the set points of the data and indicates a very good fit. Similarly, R^2 values closest to 1 indicates very high degree of fit of the predicted response to the actual data. Generally, analysis of the results as obtained from Tables 1 through 3 reveals that NARX-1 modeling gave the best performance in terms of MSE and R^2 values for training, validation and testing. The overall best configuration was that of NARX-1 with 1-time delay and 20 neurons with a distinctive metric performance of MSE and R^2 values all lower than 0.01 and greater than 0.99. Thus, the NARX-1 model with 20 neurons was then selected as the best configuration, and then used for forecasting in this study. It is clearly seen from the effects of the hidden neurons for each time delay analysis of the obtained results from Figures 6 through 8, that an increase of the hidden neurons produced varying MSE and R^2 values for training, validation and testing for the NARX network. It was generally seen that the MSE value for testing was much larger than that for training and validation sets which could be due to the small volume of dataset apportioned to it. The low values of MSE of testing which were generally close to the MSE of training signified an accurate model performance by the NARX model network. Specifically, the NARX model with a 1-time delay exhibited the lowest values for both training and validation, highlighting its superior performance.

3.2.3. Performance evaluation of NARX-1 model

The result of the evaluation of the performance of NARX-1 model based on number of epochs is presented in Figure 9 while performance evaluation in terms of autocorrelation of errors are as presented in Figure 10. The time series plot in Figure 11 presents detail insight into the NARX-1 model as function of output and target parameters. The epochs as can be seen in Figure 9 serves as a parameter representing the number of passes the LM algorithm makes over the complete training dataset. Each epoch involves a series of iterative processes to evaluate the models performance, continuing until the optimal performance is achieved. From Figure 9, it is evident that the dataset underwent 12 epochs and that the MSE decreases for training, validation, and testing as the number of epochs increases. Notably from the result of Figure 9 is that the best performance for the NARX-1 model is achieved at epoch 6 with an MSE value of 6.24×10^{-23}. Similarly, performance evaluation result as presented in Figure 10 in terms of autocorrelation errors, shows that the autocorrelation error for the NARX-1 model falls within the 95% confidence interval, indicating the presence of a white noise process. It should be noted that understanding how data observations in a sequence affect each other in time series modeling can enhance model's generalization that contributes to robust predictions of final natural gas demand. Autocorrelation, which involves analyzing lagged values of a time series, is therefore crucial. The time series plot result as presented in Figure 11 provides a detailed insight into the NARX-1 model as function of output and targets parameters. It is evidently clear from Figure 11 that the NARX-1 algorithm effectively trains the dataset. The residual errors from the training, validation, and testing output and targets are all less than 10%. This therefore suggests that the NARX-1 model is well suited for modeling the prediction of natural gas demand.

3.2.4. Pattern trend analysis

The result as obtained from Figure 12 shows the regression analysis to compare the actual data and the predicted target out response. The result shows the non-linear fitting of the actual data and the predicted output response of the NARX-1 model and equally reveals the capacity of the Levenberg –Marquardt training algorithm to fit the actual data to the predicted target output based on the input variables. A careful observation of Figure 12, clearly shows that the predicted response output from NARX-1 model clearly follows the path of the actual data indicating that the model is able to capture the general trend and patterns of the actual data and the input variables. The close alignment between the trend lines suggests that the model has been successful in predicting the target output values with a high degree of accuracy. This is also reflected in the low and high values of MSE and R^2 as shown in Table 4

3.2.5. Forecasting ability of NARX-1 model

The forecasting ability of NARX-1 model as presented in Table 5 shows the obtained future values of the average annual natural gas demand forecast result for the NARX-1 model while Figure 13 illustrates the average annual natural gas demand for from the year 1975 to 2033. The obtained result from Table 5 shows that the forecasted values of the average annual natural gas demand for the 10 years period from 2024 to 2033 falls between 12 bcm to 18 bcm for the 10 years forecast period. The obtained result in this study compares favourably well with that of the study by Ayodele *et al.* [26]. Similarly, result from Figure 13 shows the average annual natural gas demand from the year 1975 to 2033 that comprises the integration of the input data and the forecasted future values. The result from Figure 13 clearly shows that the average annual natural gas demand shows seasonal variation with year in the region increasing and decreasing alternately with time. However, the increase within the 10 years period did not reach nor exceed the peak value record in 2015 which was 18.445 bcm.

4. Conclusion

Based on the obtained results and discussions on this study, the capability of the non-linear autoregressive exogenous neural network (NARX) model as a valuable tool for predicting the average natural gas demand in Nigeria is emphasized. The obtain result from sensitivity analysis on neuron sizes based on the number of time delays for NARX-1, NARX-2, and NARX-3, generally shows that the performance of the NARX model decreases with an increase in the number of network time delays and that NARX-1configuration with one network time delay and 20 neurons exhibited the highest performance with the lowest MSE value and highest R^2 value. However, it is concluded that the NARX model have that aptitude for discerning complex correlations within dataset, and that the chosen NARX-1 model for this study showcases higher accuracy and efficiency in modeling the non-linear relationship between input variables and natural gas demand. The autocorrelation and pattern trend analysis equally confirmed the robustness of the NARX model and in particular the NARX-1 model in capturing the temporal dependencies within the time series data and visually demonstrated the close fit of the model to the actual data, therefore, translating to accurate prediction. The forecasting capability of the selected NARX-1 model as investigated through a 10-year period, revealed the future values of the average annual natural gas demand in Nigeria to follow a consistent upward trend, aligning with the expected growth in population, GDP per capita, and a reduction in natural gas prices. It is then concluded that the comprehensive analysis conducted in this study can significantly contribute valuable insights for policy makers, energy planners and researchers involved in energy demand forecasting to take an informed decision and strategic planning for sustainable development of Nigeria's natural gas sector.

Recommendation

Researchers and practitioners seeking to implement the NARX model for natural gas demand forecasting should appreciate the importance of using dataset that accurately represent the sample and which have been thoroughly validated. This helps to ensure that the input data used for training the model is reliable and reflects the real world dynamic of natural gas demand.

Conflict of interest. The corresponding author states that there is no conflict of interest.

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