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

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Abstract

Accurate natural gas demand forecasting is critical for ensuring efficient resource allocation, infrastructure planning, and energy security. This study presents the implementation of a NARX artificial neural network (ANN) model using MATLAB (R2022b) to forecast Nigeria's natural gas demand. The NARX model, known for its capability to handle nonlinear time series data with external inputs, was applied using key variables such as population, GDP per capita, natural gas reserves, and price, with the target output being natural gas demand. The methodology involved data sourcing, cleaning, and normalization, followed by model training with the Levenberg-Marquardt (LM) algorithm in MATLAB, validation, and testing. Three different NARX configurations (NARX-1, NARX-2, and NARX-3) were tested, with sensitivity analyses conducted on the number of time delays and neurons to optimize the model's structure. Performance was evaluated using metrics like mean squared error (MSE) and coefficient of determination (R2), with results indicating that the NARX-1 model with 20 neurons achieved the best performance, boasting an R2 of 0.988. The result showed that natural gas demand in Nigeria has steadily increased over time, with fluctuations in response to global economic crises like the 2008 recession and the COVID-19 pandemic. Sensitivity analyses revealed that the NARX-1 configuration, with 20 neurons, provided the most accurate forecasting results based on its low MSE of 0.003396 and high R^2 value of 0.988155, outperforming other models. These findings demonstrate the effectiveness of the NARX model for forecasting natural gas demand, making it a valuable tool for energy planning and decision-making in Nigeria.

Introduction

Energy plays a crucial role in the progress of societies and global economies, with its significance increasing due to factors such as economic growth, population expansion, and rapid urbanization worldwide (Toren 2023). There is a greater emphasis on energy modelling and forecasting within the energy sectors due to the government's strict energy production regulations and growing environmental concerns. A reliable and consistent energy supply is crucial for a nation's economic and societal advancement. Therefore, policymakers need to understand the future energy needs to develop a plan for the country's energy provision (Sharma et al. 2021). Predicting energy consumption and demand, considering limitations such as resource availability, fuel costs, capacity needs, and investments, has become essential for managing the rising trend of energy use.

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Natural gas has long been considered a "cleaner" alternative to traditional fossil fuels like crude oil and coal due to its lower carbon footprint (Mohammad et al. 2021). It is often regarded as a more reliable power generation option compared to renewable sources such as solar and wind, owing to its consistent availability and ability to provide stable power output regardless of weather conditions (Lehner et al. 2023). Given its reliability and accessibility, natural gas is favoured for power generation, urban heating, public transportation, and manufacturing. As the global emphasis on decarbonization and sustainability grows, natural gas is expected to continue playing a significant role as an energy source. It is anticipated to play a pivotal part in the transition from fossil fuels to "green" and renewable energies, contributing significantly to the social and economic progress of nations and aligning with sustainable energy trends (Kuzemko et al. 2020; Zhukovskiy et al. 2021; Zaytsev et al. 2022).

The energy shortage in Nigeria has been a longstanding concern for both the government and the populace (Omidih and Omotehinse 2020). Various interventions at the community, state, and national levels have had limited impact on addressing the energy challenges (Endurance et al. 2021). The Federal Government of Nigeria has made efforts to diversify the energy mix to include conventional energy generation, renewable energy technologies (RETs), and nuclear energy (Diemuodeke et al. 2021). However, despite these initiatives, the issue of energy scarcity persists, with demand for electricity outpacing supply (Bassey et al. 2022). The gas sub-sector, including power generation, petrochemicals, cement, and residential applications, has been identified as a critical area capable of driving the country's economic development (Agbonifo 2016).

Natural gas is among Nigeria's abundant indigenous energy sources, making it essential to grasp how its demand will change to support rapid economic growth (Ekwueme et al. 2022). Given the growing importance of natural gas in the global energy landscape, there exists an intriguing research opportunity in developing quantitative demand models for this essential energy source (Cai et al. 2021; Liu et al. 2023).

Forecasting natural gas demand holds immense importance in Nigeria's energy policy and planning. An inaccurate estimation of natural gas consumption can have significant repercussions, leading to economic losses for end consumers and mismanagement of supplies and infrastructure. This misestimation can result in disruptions in natural gas supply, causing substantial economic costs. For instance, disruptions in natural gas supply have led to losses in productivity in manufacturing industries, with reported losses amounting to billions of dollars (Duhalt 2022). Moreover, the nexus between natural gas consumption and economic growth is non-linear, emphasizing the importance of accurate estimations to ensure sustainable economic development (Sohail et al. 2021).

Natural gas demand forecasting is a crucial aspect of energy planning, particularly in an industry marked by risks and uncertainties. It involves utilizing models to analyse historical data and offer insights into future energy demand trends (Petkovic et al. 2021). This process primarily deals with time-series forecasting, focusing on data points sampled at regular intervals (Hurn et al. 2023). The classification of natural gas demand modelling involves criteria such as the forecasting horizon, tools used, data types, and the specific area of application (Hong 2023). The forecasting horizon can range from hourly and daily to monthly, annually, or a combination of these periods.

Methods for forecasting natural gas demand include analytical, statistical, artificial intelligence, and hybrid approaches (Manowska et al. 2021). Analytical or physical methods heavily rely on variables influencing natural gas consumption, including weather-related parameters (temperature, humidity, sunshine, wind speed), economic factors (Gross Domestic or National Product, gas prices), and demographic factors (general population, household composition, birth rate). These methods leverage mathematical equations to model interactions between input parameters and natural gas demand (Delcroix et al. 2021). However, due to the inherent non-linear nature of natural gas demand as a time series problem, analytical modelling becomes increasingly challenging (Rahmoune et al. 2021). This complexity has driven the development of new research techniques, such as statistical methods and artificial intelligence methods, as well as hybrid approaches, to address the evolving demands of forecasting in the energy sector.

Artificial neural networks (ANNs) are widely used for natural gas demand forecasting, alongside other AI techniques like support vector machines, adaptive neurofuzzy inference systems (ANFIS), long short-term memory (LSTM), and meta-heuristic algorithms such as genetic algorithms and particle swarm optimization algorithms (Panapakidis and Dagoumas 2017). ANNs are preferred due to their superior accuracy, especially in handling nonlinear datasets without predefined hypotheses. Understanding ANN architecture, including the combination and activation functions, is essential for effective utilization. Various ANN algorithms, such as multilayer perceptron (MLP), radial basis function neural network (RBF), and general regression neural network (GRNN), are commonly used for energy demand forecasting (Aruta et al. 2022). Dynamic ANNs, including recurrent neural networks like NAR, NARX, and LRN, are also effective in estimating nonlinear input-output correlations in time sequence data (Hassan et al. 2021).

In this study, we employ a non-linear autoregressive with exogenous input (NARX) neural network model for natural gas demand forecasting. This model utilizes a multivariate approach incorporating input variables such as population, GDP per capita, average natural gas price, and gas reserves, with data specific to Nigeria.

Materials and Method

Materials. The implementation of the NARX ANN modelling was conducted using MATLAB (R2022b). MATLAB has various toolboxes specifically designed for neural network modelling, which covers areas such as neural net fitting, clustering, pattern recognition, and time series models. Neural net time series toolbox (in MATLAB) was deployed to address this nonlinear time series problem.

Methods. The method employed in this study involves modelling and simulation to achieve the desired objectives. Specifically, the NARX model principle, its implementation strategy, and simulation processes are described in detail. The overall methods can be succinctly summarized through the block diagram provided in **Figure 1**.

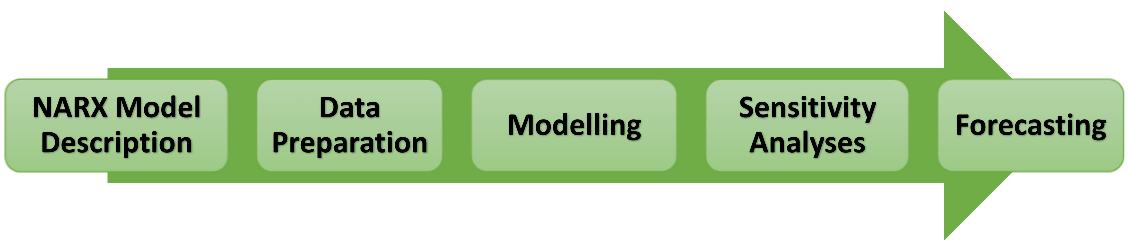


Figure 1—Methodology flowchart.

The process begins with an explanation of the NARX model and its fundamental equation, followed by data preparation steps like sourcing, cleansing, and normalization to refine the dataset. Then, modelling involves training, validation, and testing, with sensitivity analyses determining the optimal model structure for forecasting based on input variables.

ANN NARX Model. The NARX neural network, which stands for Non-linear Autoregressive Exogenous with External input, is a dynamic tool for time series modelling. It distinguishes itself by incorporating external inputs, enabling it to analyse relationships among current and past values of a time series and external data. With its high memory capacity, it effectively captures time-varying patterns in datasets (Alsumaiei 2020). **Eq. (1)** provides the mathematical representation of the NARX model, predicting the output f(t) based on input parameters x(t) and past values of the series y(t) and x(t).

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

The NARX model operates on the principle that the current value of y(t) is influenced by past values of both y(t) and x(t) (Necesito et al. 2022). In this model, inputs are linked to network weights, and adjustments to hidden neurons occur iteratively for different time delays. Network configuration is chosen to minimize mean square error (MSE). The hidden layer includes weight matrices connecting to other layers, each associated with specific inputs and biases based on weight function rules. The net input, formed by combining the outputs of these weight functions with the bias using the net input function rule, drives the network.

The NARX network is trained using MATLAB's Neural Net Time Series Toolbox, employing the hyperbolic tangent sigmoid function for activation in both hidden and output layers. Performance is assessed using metrics like MSE and R^2. Successful training is indicated by minimal MSE and a high R^2 value, ensuring the model's effectiveness for forecasting.

Data Sourcing and Preparation. The dataset utilized in this study includes key inputs such as Nigeria's population, GDP per capita, natural gas price, and reserves, with the target output being natural gas consumption demand. Covering the period from 1975 to 2023, the data were obtained from multiple credible sources: population figures from the National Population Commission (NPC), GDP per capita data from the National Bureau of Statistics (NBS), natural gas prices from the Henry Hub Natural Gas Spot Price statistics, natural gas reserves from the Nigerian Upstream Petroleum Regulatory Commission (NUPRC), and natural gas demand metrics from the Nigeria Gas Company (NGC). This comprehensive dataset serves as the foundation for modeling and forecasting natural gas demand in Nigeria.

Before training, thorough data cleaning and normalization were conducted to rectify errors and eliminate noisy data points. The specific dataset used for simulation is detailed in **Table 1**. The simulation dataset comprises forty-nine data points for both the input and target output datasets.

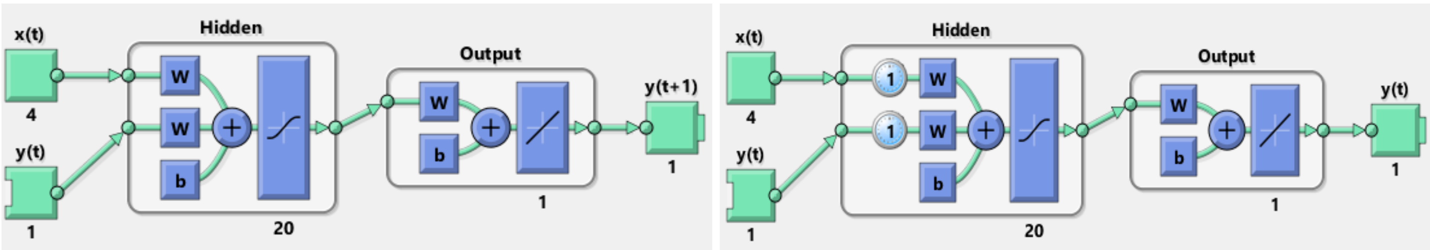
Table 1—Simulation data.

Year	Population, billion	GDP Per Capita M$/person	NG Reserves TCM	NG Price, $/Mmbtu	NG Demand, BCM
1975	0.0710	0.442	1.2546	0.43	0.4000
1976	0.0727	0.562	1.24611	0.58	0.6300
1977	0.0746	0.541	1.224	0.79	0.5000
1978	0.0765	0.532	1.203	0.91	0.3800
1979	0.0786	0.668	1.183	1.18	1.3800
1980	0.0807	0.88	1.16114	1.59	1.0702
1981	0.0828	2.188	1.14698	1.98	2.1524
1982	0.0848	1.845	1.38501	2.47	1.4160
1983	0.0868	1.224	1.37	2.59	2.2996
1984	0.0888	0.903	1.355	2.66	2.7471
1985	0.0908	0.882	1.34	2.51	3.0586
1986	0.0929	0.639	2.4	1.94	3.2852
1987	0.0952	0.598	2.407	1.66	3.7015
1988	0.0974	0.55	2.476	1.68	3.7706
1989	0.0998	0.474	2.832	1.7	4.7007
1990	0.1022	0.568	2.84	1.7	3.7100
1991	0.1046	0.503	3.4	1.49	4.7579
1992	0.1071	0.477	3.7162	1.77	4.9007
1993	0.1096	0.27	3.683	2.12	5.0507
1994	0.1121	0.321	3.45	1.92	4.5506
1995	0.1147	0.407	3.474	1.72	5.1906
1996	0.1173	0.46	3.475	2.73	5.4608

1997	0.1201	0.479	3.483	2.48	5.8508
1998	0.1229	0.468	3.512	2.09	5.9008
1999	0.1257	0.496	3.512	2.27	6.2109
2000	0.1287	0.565	4.106	4.31	6.7310
2001	0.1317	0.587	4.6327	3.96	6.2109
2002	0.1348	0.734	4.9973	3.36	6.3609
2003	0.1380	0.787	5.055	5.49	8.5112
2004	0.1413	0.993	5.2289	5.89	9.3213
2005	0.1447	1.25	5.1518	8.92	10.3615
2006	0.1483	1.652	5.207	6.72	10.9215
2007	0.1519	1.876	5.292	6.98	10.6015
2008	0.1557	2.228	5.292	8.86	12.2767
2009	0.1597	1.884	5.292	3.95	9.8457
2010	0.1637	2.28	5.1775701	4.39	5.0307
2011	0.1679	2.505	5.1755877	4	5.4008
2012	0.1722	2.728	5.1183801	2.75	14.3070
2013	0.1766	2.977	5.1070518	3.72	15.6932
2014	0.1819	3.201	5.3239875	4.37	18.3704
2015	0.1871	2.68	5.2842779	2.61	18.4446
2016	0.1924	2.145	5.4752043	2.49	18.1679
2017	0.1977	1.942	5.62687	2.96	12.7952
2018	0.2030	2.126	5.6749974	3.16	10.7556
2019	0.2033	2.334	5.626	2.57	12.7050
2020	0.2083	2.075	5.674	2.01	14.3610
2021	0.2134	2.066	5.76	3.85	15.1652
2022	0.2185	2.184	5.832	6.45	15.6425
2023	0.2262	0.211	5.91	2.57	15.9922

The NARX Modelling Technique. The modelling and forecasting of average annual natural gas demand was conducted using the NARX Model. Three distinct NARX configurations, denoted as NARX-1, NARX-2, and NARX-3, were analysed, with the numerical suffix indicating the number of time delays in each configuration. These time delays play a crucial role in measuring dataset autocorrelation, filtering nonlinear data, and aiding in prediction. Moreover, sensitivity analyses were performed on the number of neurons, exploring configurations with 5, 10, 15, and 20 neurons, respectively. The performance of the NARX models was systematically compared, and the most effective model, determined by considering both time delays and the number of neurons, was selected for forecasting. 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 depicted in **Figure 2(a)**, while the step-ahead predictions (forecasting) are illustrated in **Figure 2(b)**. Figure 2(a) illustrates the structure of the training model, with x(t) representing the input data and y(t) indicating the target (actual data) at 1. The artificial neural network time series model engages in simulation by analyzing the input and target to create a model that generates the modeled target y(t) from the provided output data during training. Implementation of the NARX model involves introducing a time delay, which excludes a certain number of data points from the beginning of the dataset. Specifically, a time delay of 1:1 means one data point was omitted from both the predicted output response (x(t)) and the actual response (y(t)) after training. Additionally, the step-ahead prediction of the NARX model incorporates an additional future value, one step ahead, into the predicted output data, accounting for the forecasted value.



(a) Open-loop view for training (b)One-step ahead prediction view

Figure 2—ANN NARX Neural network.

Model Performance Evaluation Metrics. The model's performance was evaluated using several metrics, such as mean squared error (MSE), coefficient of determination (R^2), root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).
The formulas for these statistical parameters are as follows:

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

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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{p,i}-x_{a,i}\right)^2}, \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(x_{a,i}-x_{p,i}\right)\right|, \quad (5)$$

$$MAPE = \frac{\frac{1}{n}\sum_{i=1}^{n}\left|\left(x_{a,i}-x_{p,i}\right)\right|}{\frac{1}{n}\sum_{i=1}^{n}x_{a,i}} \quad (6)$$

Where n is the number of experimental runs, $x_{p,i}$ is the estimated values, $x_{a,i}$ is the experimental values, $x_{a,ave}$ is the average experimental values.

Results and discussions

Time Series Data Trends. The trends in the time series data were evaluated by plotting both the input and target output variables against the year. **Figure 3** displays the trend of the time series data. In general, the analysis reveals a rising trend in natural gas demand over time, with notable declines in 2010, 2019, and 2020 due to global economic downturns such as the 2008 recession and the COVID-19 pandemic which impacted various economies and led to reduced natural gas prices in 2009. This demand is paralleled by continuous growth in population and natural gas reserves. Additionally, the GDP per capita of Nigeria shows fluctuations over time, with distinct phases of growth and decline, ultimately stabilizing at a relatively constant level.

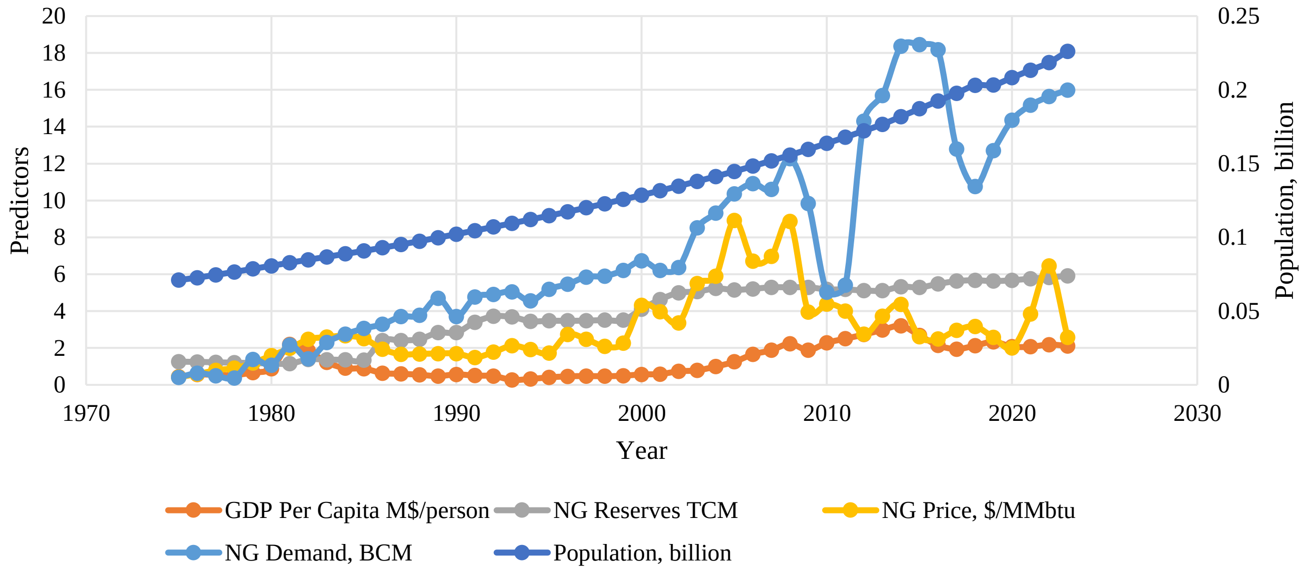


Figure 3—Trend of time series data.

Modelling Sensitivity Analysis. Sensitivity analyses were conducted to examine time-delays and the number of neurons, aiming to evaluate the parametric sensitivity of the models and understand the relationship between input variables and the target output response. **Table 2** provides a summary of the results for the NARX-1 model. The analysis of Table 2 reveals that the optimal number of neurons for the NARX-1 model configuration is twenty. This conclusion is drawn from the more favorable training, validation, and testing mean squared error (MSE) and coefficient of determination (R^2) values compared to other neuron sizes. Specifically, in the NARX-1 simulation with twenty neurons, it was observed that the training MSE was lower than that for validation and testing.

Table 2—Detailed analysis of NARX-1 configuration to determine the optimal 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**

From **Table 3**, it is evident that the optimal configuration for NARX-2, based on the training, validation, and testing MSE and R^2 values, indicates that the most suitable number of neurons is twenty. This selection is justified by its combination of the lowest MSE and favorable R^2 value. Therefore, for NARX-2, it is recommended to utilize twenty neurons to achieve a representative and accurate forecast.

Table 3—Detailed analysis of NARX-2 configuration to determine the optimal hidden neuron.

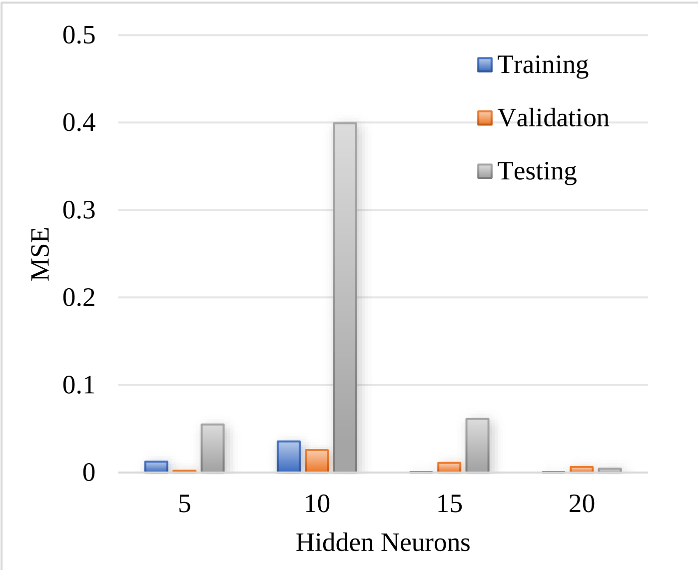
Hidden Neurons	Training		Validation		Testing	
	MSE	R^2	MSE	R^2	MSE	R^2
5	0.01272	0.95707	0.00546	0.96256	0.03637	0.85711
10	0.00867	0.97535	0.01063	0.96176	0.08585	0.90522
15	0.03552	0.91218	0.01640	0.96999	0.06402	0.95897
20	**0.00936**	**0.97063**	**0.01877**	**0.98297**	**0.06082**	**0.95263**

Table 4 indicates that the NARX-3 model performs best with ten neurons, based on lower MSE values and higher R^2 values across training, validation, and testing datasets. However, a comprehensive examination of Tables 2, 3, and 4 demonstrates that the NARX-1 model consistently outperforms others in terms of MSE and R^2 values. This specific setup consistently achieves R^2 values exceeding 0.99 and MSE consistently below 0.01, indicating exceptional performance. Consequently, the NARX-1 model with twenty neurons is chosen as the optimal configuration for forecasting natural gas demand.

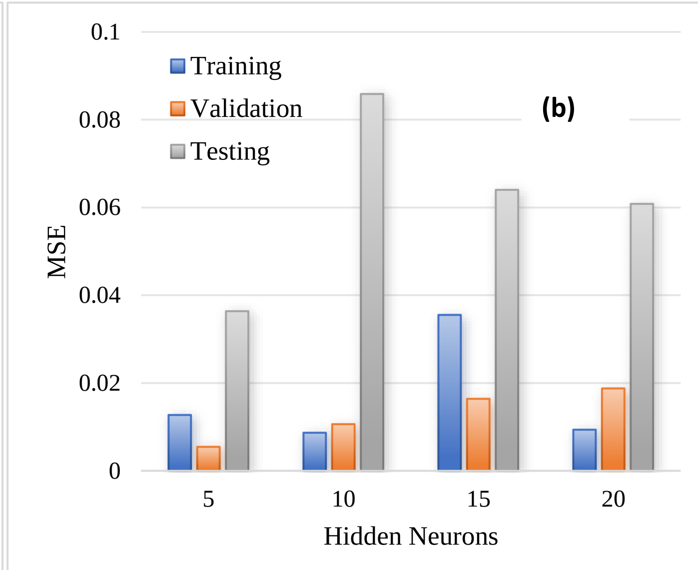
Table 4—Detailed analysis of NARX-3 configuration to determine the optimal hidden neuron.

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

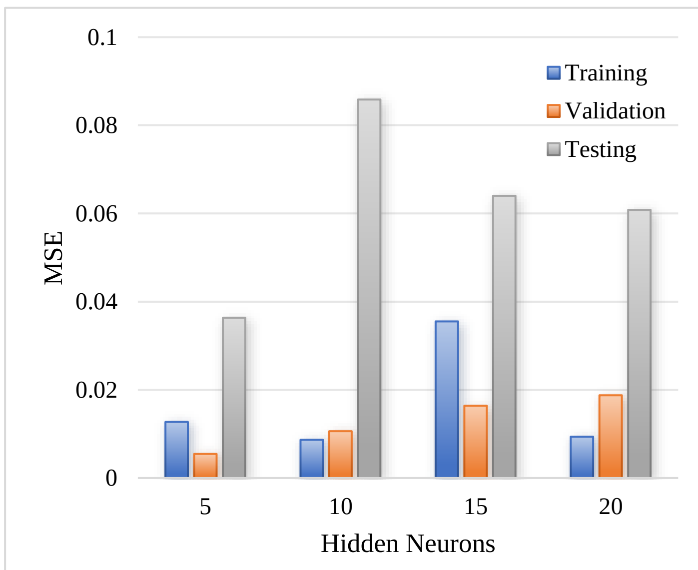
As shown in **Figure 4**, the increase in hidden neurons led to different mean squared errors (MSE) for the training, validation, and testing phases of the NARX network. Notably, the testing MSE appeared significantly larger than that of the training and validation sets, potentially due to the smaller dataset volume allocated for testing. The consistently low testing MSE values, closely aligned with the training MSE, suggest accurate model performance by the NARX network. Specifically, the NARX model with a 1-time delay exhibited the lowest MSE values for both training and validation, highlighting its superior performance.



(a) NARX-1



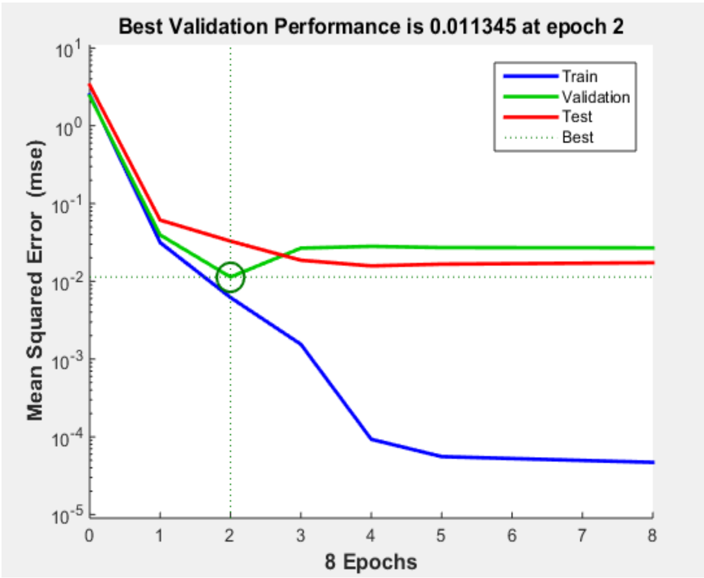
(b) NARX-2



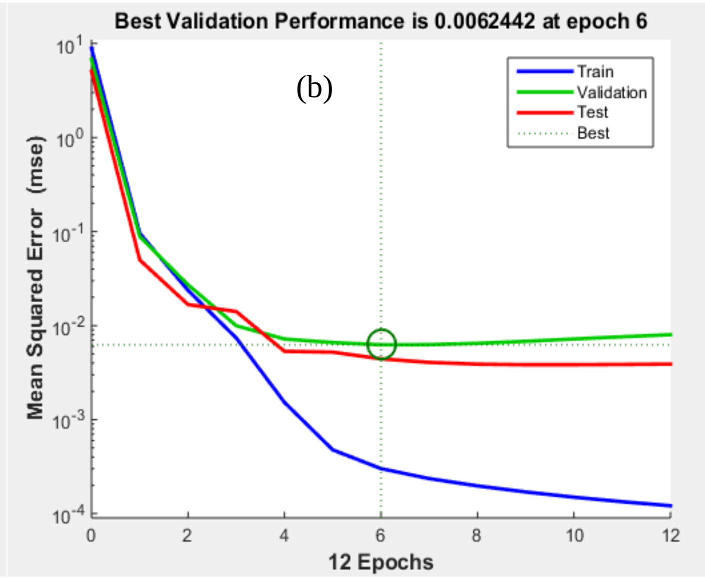
(c) NARX-3

Figure 4—Determination of hidden neurons for NARX model using different models.

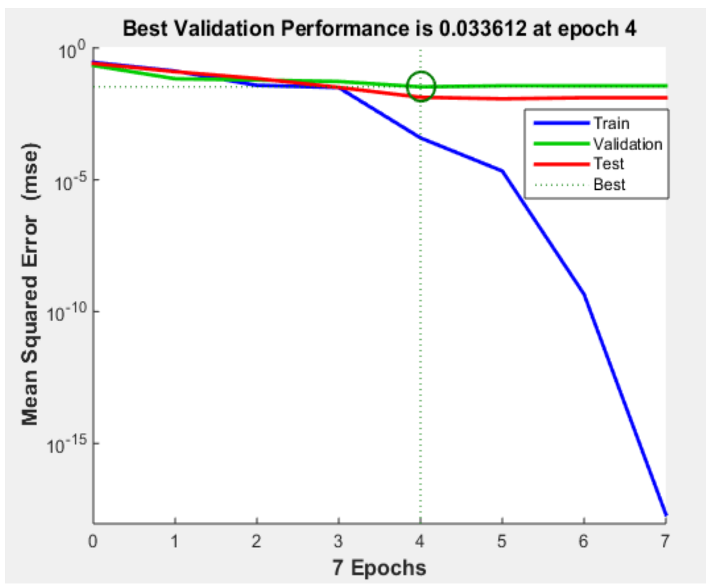
Performance Evaluation of NARX Models. This section evaluates the performance of three NARX models: NARX-1, NARX-2, and NARX-3. Throughout the training process, the entire dataset experienced multiple passes referred to as epochs. An epoch serves as a parameter denoting the number of passes the LM algorithm makes over the complete training dataset. Each epoch involves a series of iterative processes to assess the model's performance, continuing until optimal performance is attained. In **Figure 5(a)**, the dataset underwent 12 epochs, while for **Figures 5(b)** and **5(c)**, the datasets underwent 8 and 7 epochs, respectively.



(a) NARX-1



(b) NARX-2

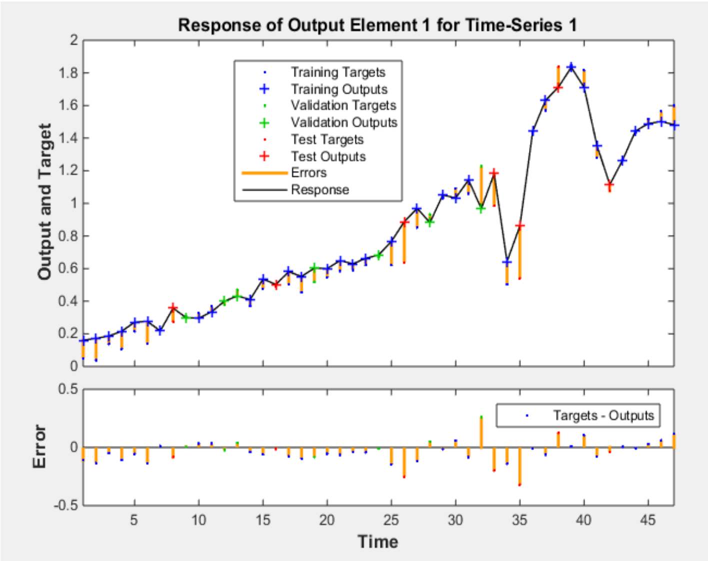


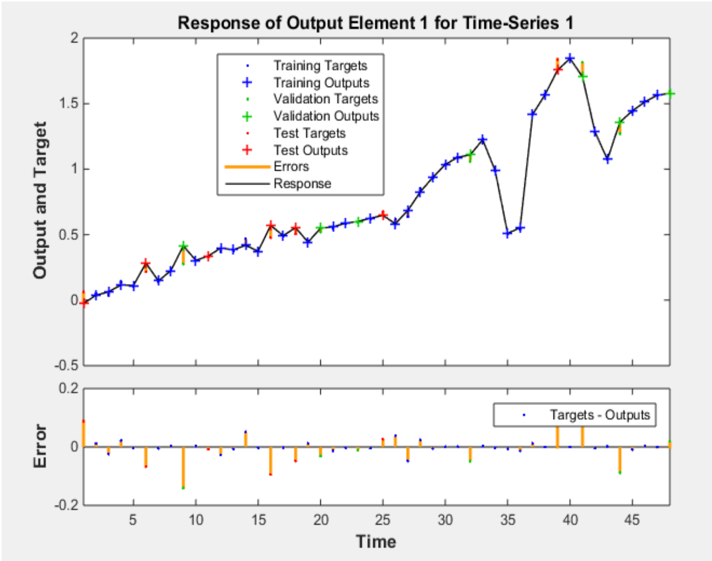
(c) NARX-3

Figure 5—Determination of the best validation performance for various models.

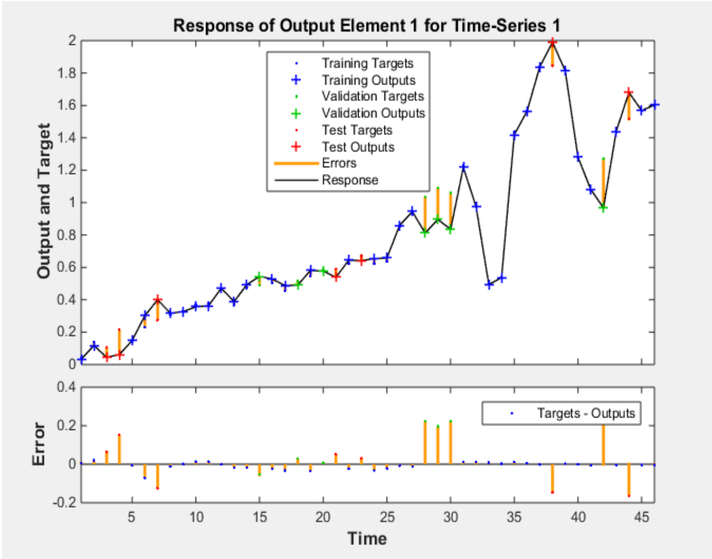
In **Figure 5**, the validation performance of NARX-1, NARX-2, and NARX-3 models is analyzed. The Mean Squared Error (MSE) decreases across training, validation, and testing datasets with increasing epochs for each model. Notably, the optimal performance for NARX-1 is observed at epoch 8 with an MSE of 6.24×10^{-3}, for NARX-2 at epoch 2 with an MSE of 1.134×10^{-2}, and for NARX-3 at epoch 3 with an MSE of 3.36×10^{-2}. The decreasing trend of MSE curves indicates prevention of overfitting.

The time series plots in **Figures 6(a)** to **(c)** offer detailed insights into the NARX models in terms of output and target parameters. In Figure 6(a), it is evident that the NARX algorithm effectively trains the dataset, with residual errors from the training, validation, and testing outputs and targets all falling below 10%. This indicates that the NARX-1 model is well-suited for modelling the prediction of natural gas demand. Similarly, the NARX model with a time delay of two, as depicted in Figure 6(b), demonstrates significant potential in predicting both targets and outputs. The training, validation, and testing of the dataset show minimal residual errors, confirming the suitability of NARX-2 network configurations for time series modelling of natural gas demand. Figure 6(c) further illustrates that the NARX model with a 3-time delay configuration is also appropriate for predicting natural gas demand, supported by the minimal residual errors observed in the training, validation, and testing outputs and targets.





(a) NARX 1 (b)NARX 2



(c) NARX-3

Figure 6—Time series-based prediction of average annual natural gas demand for various models.

Pattern Trend Analysis of NARX Models. This section examines a regression analysis comparison between actual data and predicted target output responses for the three NARX models: NARX-1, NARX-2, and NARX-3. **Figure 7** illustrates the non-linear fitting of actual data and the predicted output responses of the NARX-1 model. The figure demonstrates the capability of the Levenberg-Marquardt training model to fit the actual data to the predicted target output based on the input variables.

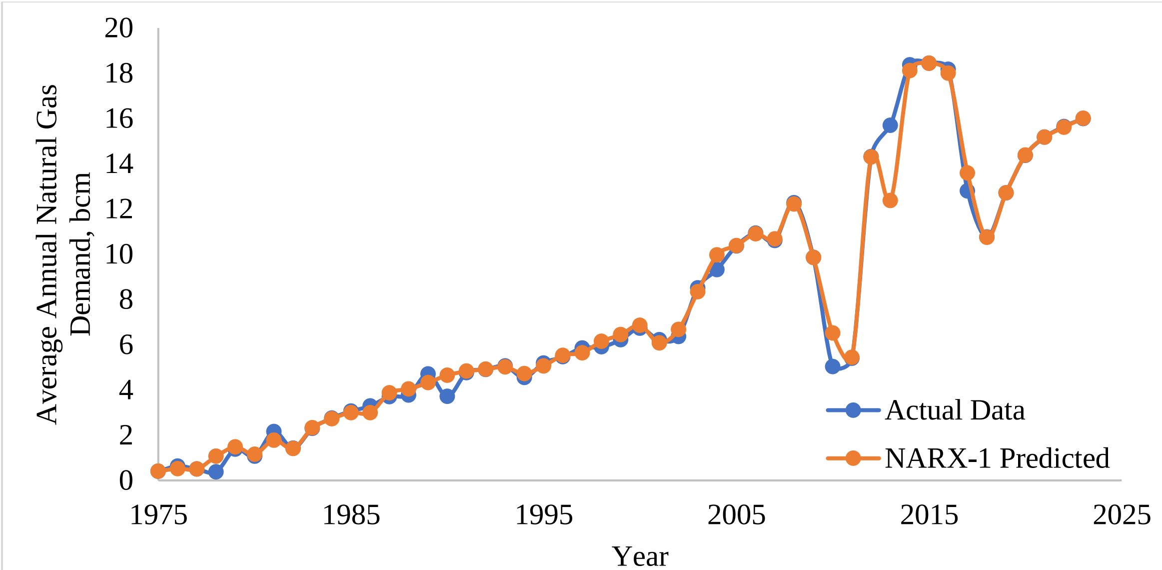


Figure 7—Comparison of the pattern of actual and predicted average natural gas demand for the NARX-1 model.

Observing Figure 7 reveals that the predicted response output from the NARX-1 model closely mirrors the path of the actual data used for training, with minimal deviations. This observation suggests that the model effectively captures the general trend and patterns of the actual data and input variables. The close alignment between the trend lines indicates that the model has successfully predicted the target output values with a high degree of accuracy. Therefore, Figure 7 illustrates that the NARX-1 model, trained by the Levenberg-Marquardt algorithm, has effectively modelled the nonlinear relationship between the variables (including population, GDP per capita, natural gas reserves, and the average annual natural gas price as inputs, and the annual average natural gas demand as the target output).

Figure 8 displays the trendline pattern of the NARX-2 model, illustrating the relationship between the actual data and the predicted target output. Trained using the Levenberg-Marquardt algorithm, the model closely aligns its predictions with the actual data, indicating successful pattern recognition and effective capture of the input-output relationship.

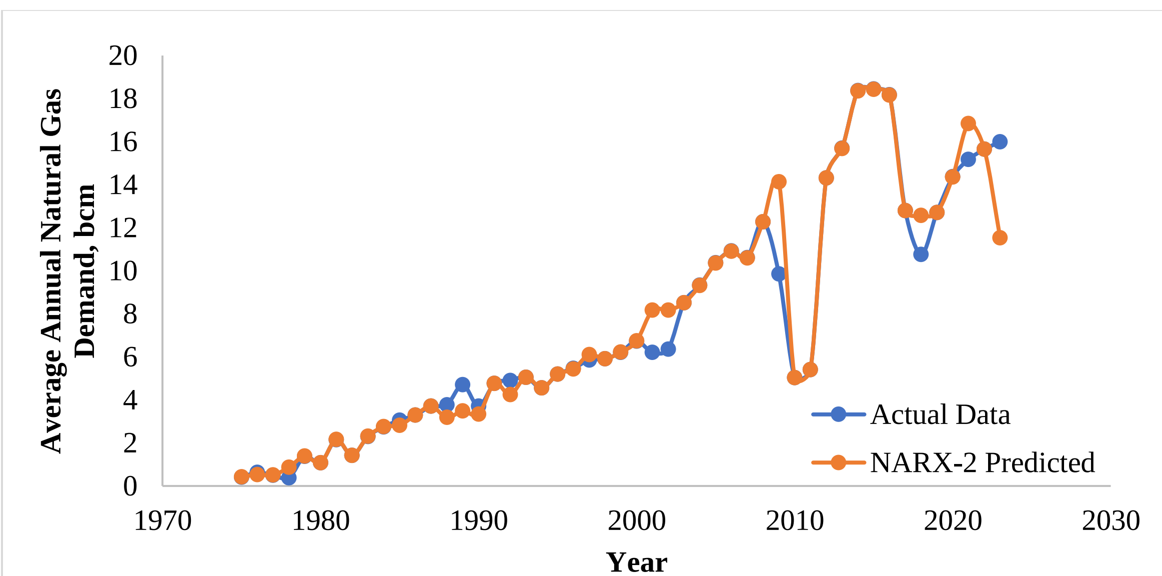


Figure 8—Comparison of the pattern of actual and predicted average natural demand for the NARX-2 model.

Figure 9 compares the pattern trendlines of the actual data with the predicted target output of the NARX-3 model, demonstrating its accurate modelling. This highlights the robustness of the NARX-3 model in effectively capturing the input-output relationship.

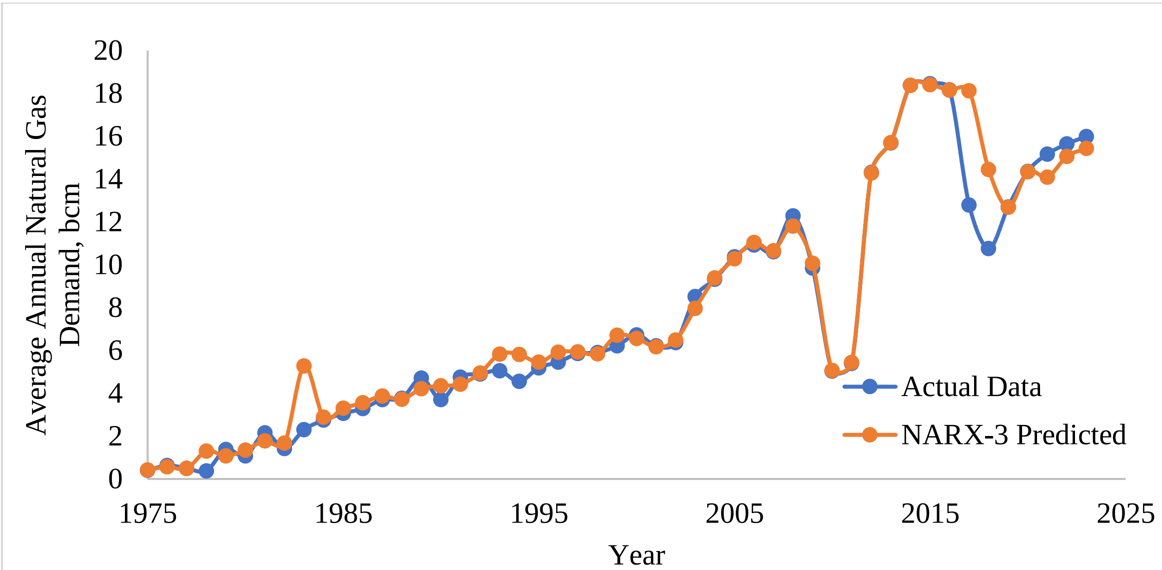


Figure 9—Comparison of the pattern of actual and predicted average natural demand for the NARX-3 model.

Table 5 indicates that the NARX-1 model outperforms NARX-2 and NARX-3 across all metrics considered. Notably, NARX-1 demonstrates a lower MSE (0.003396) and a higher R^2 (0.988155) compared to the other models. Additionally, NARX-1 exhibits lower RMSE, MAE, and MAPE values. Consequently, NARX-1 is chosen for forecasting, while NARX-3 performs the least. These findings contrast with those of (Ayodele et al. 2021), who found better performance in NARX models with higher time-delays.

Table 5—Overall performance summary of the NARX models.

Metric	NARX-1	NARX-2	NARX-3
MSE	0.003396	0.011074	0.011862
RMSE	0.058271	0.105233	0.108911
MAE	0.025333	0.041191	0.049559
MAPE	0.079376	0.080255	0.145622
R^2	0.988155	0.961953	0.961411

Forecasting Performance of NARX Model. The NARX-1 model, identified as the best-performing among the NARX models, was chosen for forecasting average annual natural gas demand. **Table 6** presents the forecasted values of future average annual natural gas demand based on the predictions made by the NARX-1 model. Table 6 displays the projected values of average annual natural gas demand over a 10-year period from 2024 to 2033. The forecasted natural gas demand ranges between twelve to eighteen billion cubic meters (bcm) for the specified decade.

Table 6—Forecasted average annual natural gas demand.

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

Table 7 compares the performance of the NARX model in this study with similar studies in the literature, specifically focusing on forecasting energy demand. The NARX-ANN model utilized in this study demonstrates robust predictability, outperforming many other models with an R2 value of 0.988. This underscores the accuracy of the average natural gas demand forecast, with minimized prediction errors.

Table 7—Comparison of the performance of the NARX model in this study and literature.

Modelling Technique	Country	Forecasting target	Performance	Reference
NARX model	Nigeria	Average Annual Natural Gas Demand	0.98816	This Study
NARX model	Malaysia	Long term Final Energy Demand per Capita	0.99	Ayodele et al. 2021
NARX model	USA	Short-Term and Medium-Term Uncertainty for Electrical Load and Wind Speed	0.9964	Jawad et al. 2018
NARX model	Nigeria	Forecasting Volatility of Nigerian Crude Price	0.986	Gulumbe et al. 2016
NARX model	Algeria	Forecasting Natural Gas Prices	0.8918	Sahed et al. 2020

Conclusions

The study utilized the non-linear autoregressive with external input (NARX) model to forecast the average annual natural gas demand in Nigeria. The NARX-1 configuration demonstrated superior accuracy with an R^2 of 0.988, outperforming other configurations. Long-term projections indicated a consistent upward trend in natural gas demand, aligning with expected economic and demographic growth factors. The findings highlight the effectiveness of the NARX model in energy demand forecasting and its potential to inform strategic planning for Nigeria's natural gas sector. Overall, the research provides valuable insights for policymakers, energy planners, and researchers, facilitating informed decision-making and contributing to sustainable development initiatives.

Conflicting Interest

The author(s) declare that they have no conflicting interests.

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