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# PREDICTION OF SELECTED AIR POLLUTANTS CONCENTRATION INAKWA IBOM STATE REGION OF NIGER DELTA

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**Abstract -** The study developed a novel multi-gas emission analyzer to generate data for the prediction of selected air pollutants at different locations in Oron Local Government Area (L.G.A) of AkwaIbom State. The following pollutants were investigated: Methane ($CH_4$), Ammonia ($NH_3$), Hydrogen sulfide ($H_2S$), Carbondioxide ($CO_2$), and Particulate Matter ($PM_{2.5}$ and $PM_{10}$). A reconnaissance survey was carried out around the communities at the sites within the selected study area. This survey was based on the direct participation and observation. However, the concentrations of the emitted gases were identified and meticulously recorded in a centralized database accessible via the Internet.Leveraging Python libraries and Artificial Neural Network (ANN) models were developed to predict air quality parameters based on the collected data. The results revealed the optimized ANN models for each pollutant, demonstrating promising predictive capabilities. Specifically, the models showcased the architecture of6 – 50 – 1, 6 – 30 – 1, 6 – 50 – 1, 6 – 50 –1, 6 – 40 – 1, and 6 – 40 – 1 as the best predicted models for $PM_{2.5,}$ $PM_{10}$, methane, hydrogen sulfide, ammonia, and carbon dioxide respectively. These configurations signify the number of input variables, neurons in the intermediate layer, and the target variable respectively. The findings of this study hold significant implications for researchers, policy-makers, and environmental scientists aiming to comprehend and address air quality concerns in Oron L.G.A and similar settings. By providing robust predictive models, that facilitates decision making to mitigate air pollution, safeguard public health and environmental integrity.

**Keywords: air pollutants, artificial neural network, multi-gas emission analyzer,reconnaissance survey, concentrations**

## 1. Introduction

One major environmental issue that humanity is currently facing as a result of several human activities is air pollution (Manisalidis et al., 2020). According to Elzbieta (2020), air pollution is the introduction of toxic compounds into the surroundings at high concentrations to produce undesirable effects on humans, animals, and vegetation,which alters the natural balance of any ecosystem. An illustration of a country with the negative impact of these pollutants would be Nigeria, a developing country that has significant air pollution as a result of increase in population, fuel oil usage and lack of environmental regulations which gives birth to poor air quality,especially in the Niger Delta region(Tawari and Abowei,2012; Abaje et al.,2020). For instance, most of the common pollutants in Port Harcourtare$PM_{10}$, carbon monoxide (CO), nitrogen dioxide ($NO_2$), ammonia ($NH_3$), sulphur dioxide ($SO_2$), and hydrogen sulphide ($H_2S$) (Nwokocha et al., 2015).However, the presence of petroleum businesses in urban areas such as Kaduna, in Kaduna State also contributed to the degradation of air quality in this location (Abdulkareem and Kovo 2006).

Several researchers have carried out different studies on how to mitigate and predict the concentration of air pollutants in some selected locations so as to demystify the adverse effects of these pollutants on human and environment so that the government can take an important step to curb this menace. This prediction is achieved by the use of machine learning techniques. One of the machine learning techniques in use today, is an Artificial Neural Network (ANN), the use of ANN allows one to create and solve a regression model with multiple features without the need to handle complex calculations. ANN is defined as a machine learning algorithms that is used to model nonlinear relations in datasets. Its architecture is constructed from multiple layers which include hidden layers and activation functions (Itai and Avraham et al, 2022). It was reported that ANN has been compared and implemented in numerous predictive modeling applications by so many researchers and concluded that it outperformed other traditional regression models (Ali and Gravino, 2019).

Furthermore, other researchers have looked into the levels of pollutants in various areas (Masood and Ahmad, 2023; Memarianfard and Hatami, 2017; Tutak and Brodny, 2019; Mirshahvalad et al, 2020; Adib et al, 2018; Peng et al, 2022; Nehete and Patil, 2021; Ejohwonu et al, 2022; Guo et al, 2023; Kim et al, 2019; Memarianfard and Hatami, 2017). Therefore, rather than utilizing software like the Hybrid Statistical Machine or Statistical Techniques, etc., this research demonstrates the efficacy of Artificial Neural Networks in predicting the gases released into the environment. For this investigation, artificial neural networks will be used. It has been proven to be efficient, straightforward, objective, and goal-oriented, and it has produced accurate results in the assessments made by different researchers. Similarly, the vast majority of the examined researchers carried out their research in urban regions, mostly ignoring rural areas that are vulnerable to human activity.

## 2. Materials and Method

### 2.1 Study Area

Oron is one of the Local Government Areas (LGAs) in AkwaIbom State. It lies between Latitudes 4˚47'N and 4˚50'N of the Equator and Longitudes 8˚11'E and 8˚15'E of the Greenwich Meridian as shown in Figure 1. It has a population of about87,209 persons and a land area of 70km2(National Population Commission, 2006).

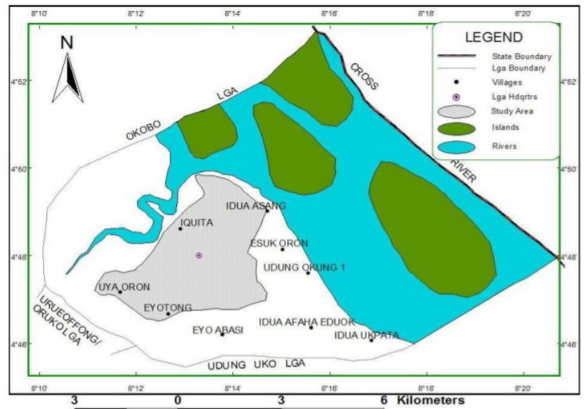


**Figure 1: Location of Oron L.GA. (Beulah and Ekong,2019).**

### 2.2 Materials

Multi-Gas Emission Analyzer also known as gas detectors was developed and used to identify different concentration of various types of gases emitted from gas flaring, vehicular emission, biomass, burning of bush, etc. It consist of plastic casing incorporated with various sensors such as, MQ2 (Carbondioxide), MQ4 (Methane), MQ136 (Hydrogen sulphide), MQ137 (Ammonia), and Particulate matters ($PM_{2.5}$ and $PM_{10}$), which is quite different from many gas analyzer because of its mobility, durability, easy to maintain, cheaper and has the capacity not only to capture the emitted gases but can also store the data capture via the internet using GPRS and store them in a database.

### 2.3 Methods

#### 2.3.1 Objective definition:

The primary objective of this research was to develop and deploy a novel multi-gas emission analyzer for accurate monitoring and assessment of air quality in the Oron Local Government Areas of AkwaIbom State.

#### 2.3.2Construction of the Multi-gasAnalyzer

The development of the multi-gas emission analyzer as shown in Figure 2, involved designing and assembling hardware components capable of measuring and storing pollutants, including Methane, Ammonia, Hydrogen sulphide, Carbon dioxide, and Particulate matters.In the course of developing the analyzer, various sensors were used. These include SDS011 air quality sensor, a DHT22 temperature and humidity sensor, and a suite of gas sensors including MQ2, MQ4, MQ8, MQ9, MQ135, and MQ136, which are strategically connected to a central NodeMCU powered by an ESP8266 microcontroller using Soldering Iron and Lead. The NodeMCU serves as the brain of the system, orchestrating data collection and coordination. Furthermore, all the captured environment data such as temperature, humidity, gas concentration, particulate matter, location, and time are sent to a database hosted on the cloud; the hardware can interact with the cloud through the Application Programming Interface (API) calls.

**Figure 2: Developed data capturing device (Gas Analyzer)**

**2.3.3 Reconnaissance survey**

A comprehensive reconnaissance survey was carried out around the communities at the sites within the selected study areas. This involved direct participation and observation to identify diverse concentrations of emitted gases.

**2.3.4 Data Collection:**

Data collection spanned a year, from 2021 to 2022, capturing temporal variations in air quality parameters. The concentrations of pollutants were meticulously recorded and stored in a centralized database accessible via the Internet.

**2.3.5 Data Analysis:**

Leveraging Python libraries, data analysis techniques were employed to pre-process and analyze the collected data. Descriptive statistics were then used to characterize the distribution and variability of pollutants.

2.3.6 **Artificial Neural Network (ANN) Model Development:**

ANN models were developed to predict air quality parameters based on the collected data. Python libraries such as Keras and scikit-learn were utilized for implementing ANN architectures.

**2.3.6.1 Model Optimization:**

The ANN models were optimized to enhance predictive capabilities. Various configurations were explored, including the number of input variables, neurons in the intermediate layer, and the target variable, to identify the most suitable architecture for each pollutant. 70% of the data set was used for training, 15% for testing,and 15% was used for validation.

**2.3.6.2 Validation and Evaluation:**

The optimized ANN models were validated and evaluated using root mean squared error (RMSE) to assess their performance and reliability in predicting air quality parameters.

Root Mean Square Error (RMSE) is a widely used metric for evaluating the performance of Artificial Neural Network (ANN) models and has several strengths.

**2.3.6.3 Implications and Applications:**

The findings of this research were discussed in the context of their implications for researchers, policymakers, and environmental scientists aiming to comprehend and address air quality concerns in Oron LGAs and similar settings.

**2.3.6.4Accessibility and Adaptability:**

The developed multi-gas emission analyzer and corresponding ANN models were designed to be accessible and adaptable, empowering stakeholders to conduct further research and devise tailored strategies for air quality management and pollution abatement initiatives in the specified locations and beyond.

## 3. Results and Discussion

### 3.1 Prediction of air pollutants for Oron L.G.A

**Table 1: Hidden neurons and RMSE of $PM_{2.5}$ for Oron**

| Number of Neurons | RMSE |
|---|---|
| 10 | 46.62 |
| 20 | 45.59 |
| 30 | 43.83 |
| 40 | 45.33 |
| 50 | 43.76 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for $PM_{2.5}$ prediction are displayed in Table 1 and also plotted on a line in Figure 3. The graph demonstrates that when the hidden neurons were set to fifty (50), the neural network performed better since 43.76 RMSE is the lowest. Therefore, 6-50-1 is the best model to forecast $PM_{2.5}$forOron. This corresponds to fifty (50) hidden neurons in the neural network, one (1) target variable ($PM_{2.5}$), six (6) input variables $PM_{10}$, temperature, relative humidity, methane, carbon dioxide, hydrogen sulphide, and ammonia), and fifty (50) hidden neurons in the neural network.

Plotting the projected values from the neural network output against the actual $PM_{2.5}$ values was done. The diagram is displayed in Figure 4:

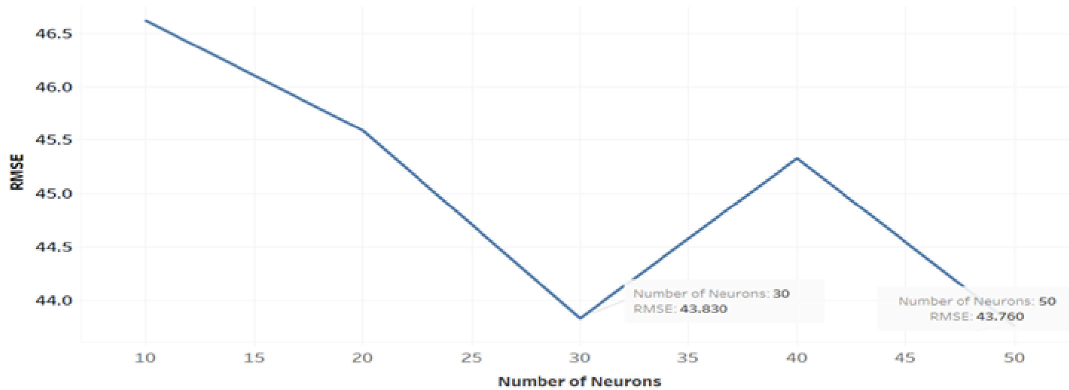


**Figure 3: Plot of hidden neurons and RMSE of $PM_{2.5}$ for Oron**

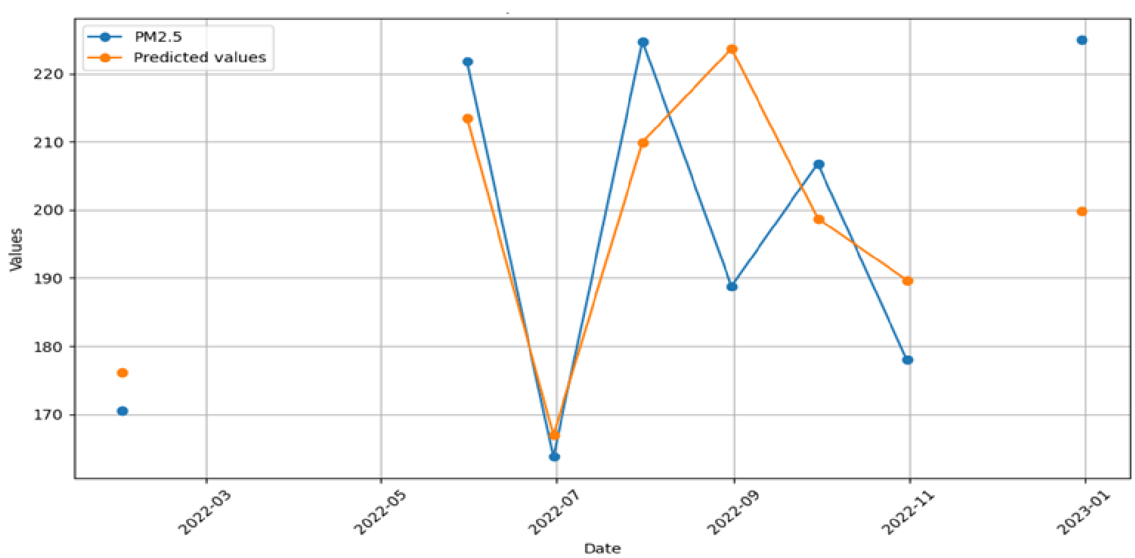


**Figure 4: Plot of observed and predicted values of $PM_{2.5}$ for Oron**

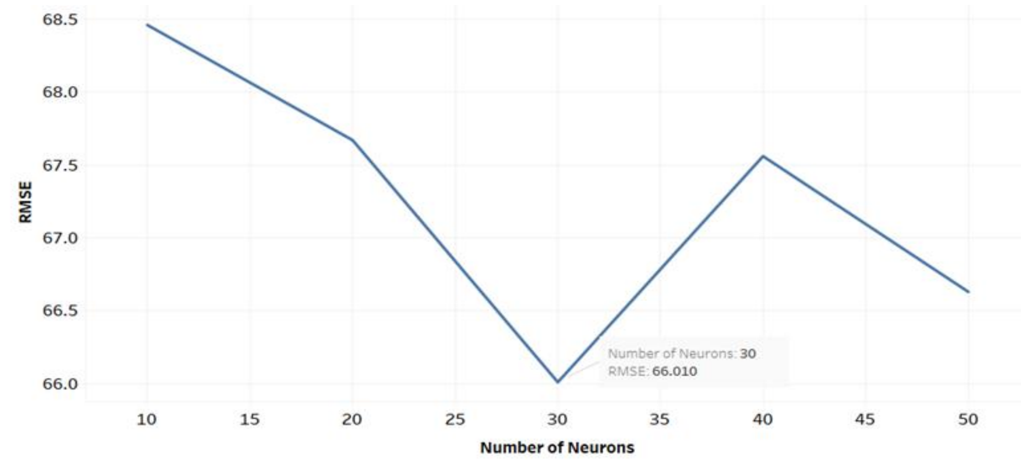


**Figure 5: Plot of hidden neurons and RMSE of $PM_{10}$ for Oron**

**Table 2: Hidden neurons and RMSE of $PM_{10}$ for Oron**

| Number of Neurons | RMSE |
|---|---|
| 10 | 68.46 |
| 20 | 67.67 |
| 30 | 66.01 |
| 40 | 67.56 |
| 50 | 66.63 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for $PM_{10}$ prediction are displayed in Table 2 and also plotted in Figure 5.

A line plot of the root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network is displayed in Figure 5. The graph indicates that when the number of hidden neurons was increased to thirty (30), ANN performed better. Therefore, 6-30-1 is the best model to predict $PM_1$0 for Oron. This equates to thirty (30) hidden neurons in the neural network, one (1) goal variable ($PM_{10}$), and six (6) input variables ($PM_{2.5}$, temperature, relative humidity, methane, carbon dioxide, hydrogen sulphide, and ammonia). The real $PM_{10}$ measurements and the neural network's anticipated output values were shown together. The diagram is displayed in Figure 6:

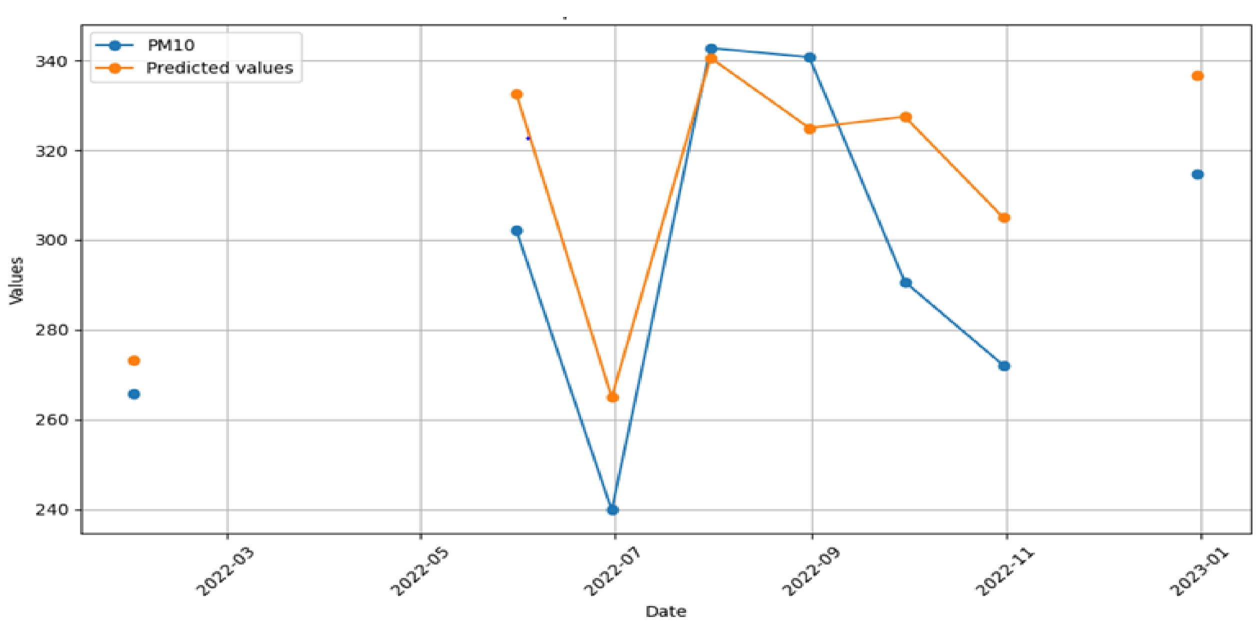


**Figure 6: Plot of observed and predicted values of $PM_{10}$ for Oron**

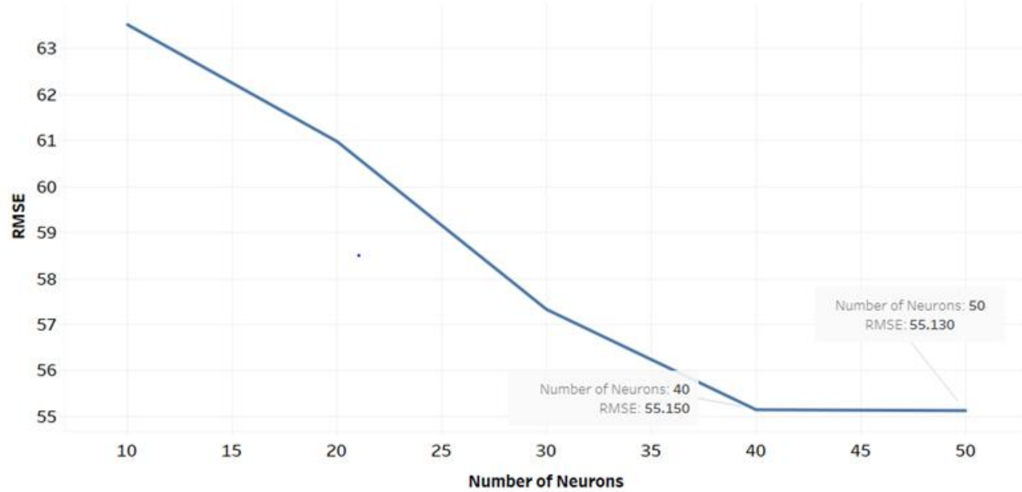


Figure 7: Plot of hidden neurons and RMSE of methanefor Oron

Table 3: Hidden neurons and RMSE of methanefor Oron

| Number of Neurons | RMSE |
|---|---|
| 10 | 63.52 |
| 20 | 60.98 |
| 30 | 57.33 |
| 40 | 55.15 |
| 50 | 55.13 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for methane prediction are displayed in Table 3 and also plotted in Figure 7.
Figure 7, displays a line plot of the number of hidden neurons employed in the network's training process about the root mean squared error (RMSE). The graph demonstrates that when the hidden neurons were set to fifty (50), the neural network performed better. Therefore, 6-50-1 is the best model to predict methane for Oron. This equates to fifty (50) hidden neurons in the neural network, one (1) target variable—methane—and six (6) input variables—$PM_{10}$, $PM_{2.5}$, temperature, relative humidity, carbon dioxide, hydrogen sulphide, and ammonia. Plotting the anticipated values of the neural network output against the actual methane readings was done. The diagram is displayed in Figure 8 :

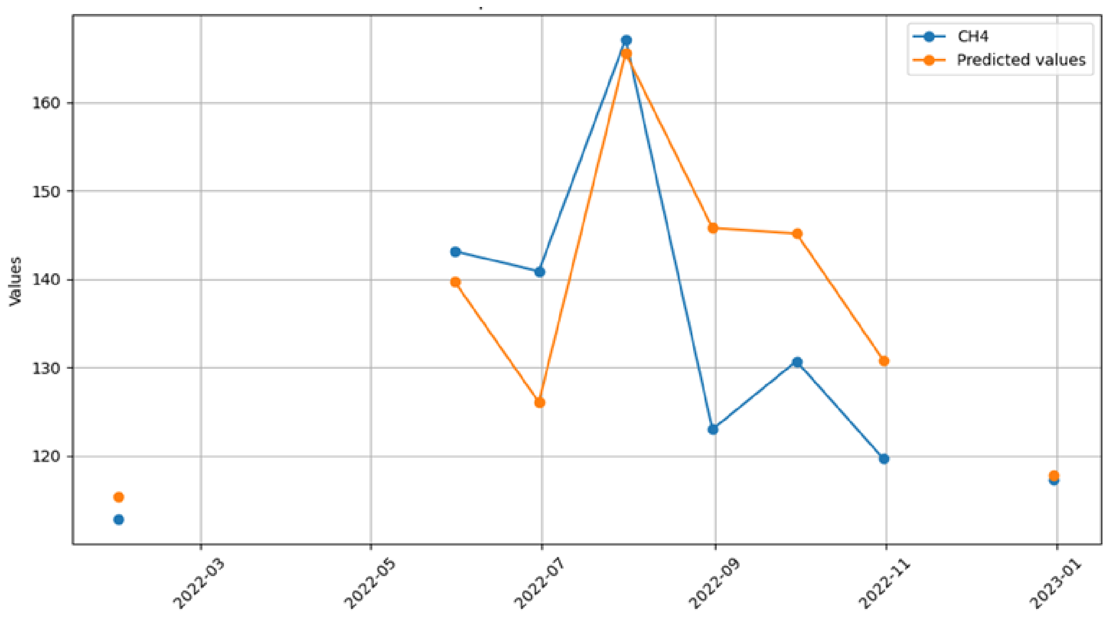


**Figure 8: Plot of observed and predicted values of methanefor Oron**

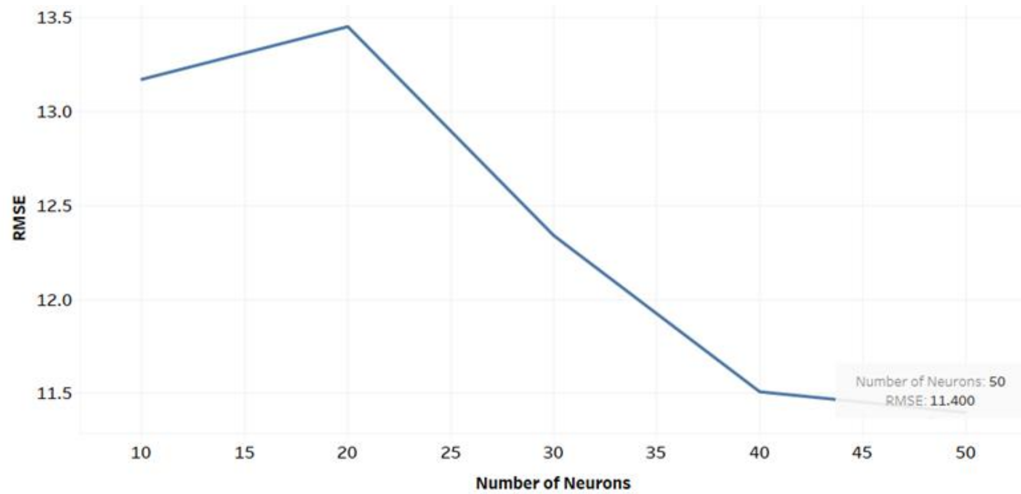


**Figure 9: Plot of hidden neurons and RMSE of hydrogen sulphidefor Oron**

**Table 4: Hidden neurons and RMSE of hydrogen sulphidefor Oron**

| Number of Neurons | RMSE |
|---|---|
| 10 | 13.17 |
| 20 | 13.45 |
| 30 | 12.34 |
| 40 | 11.51 |
| 50 | 11.40 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for hydrogen sulphideprediction are displayed in Table 4 and also plotted in Figure 9.

A line plot of the root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network is displayed in Figure 9. The graph demonstrates that when the hidden neurons were set to fifty (50), the neural network performed better. Therefore, 6-50-1 is the best model to predict hydrogen sulphide for Oron. This corresponds to fifty (50) hidden neurons in the neural network, one (1) goal variable—hydrogen sulphide—and six (6) input variables—$PM_{10}$, $PM_{2.5}$, temperature, relative humidity, carbon dioxide, and ammonia. Plotting the predicted values from the neural network output against the actual hydrogen sulphide values was done. Figure 10 shows the plot.

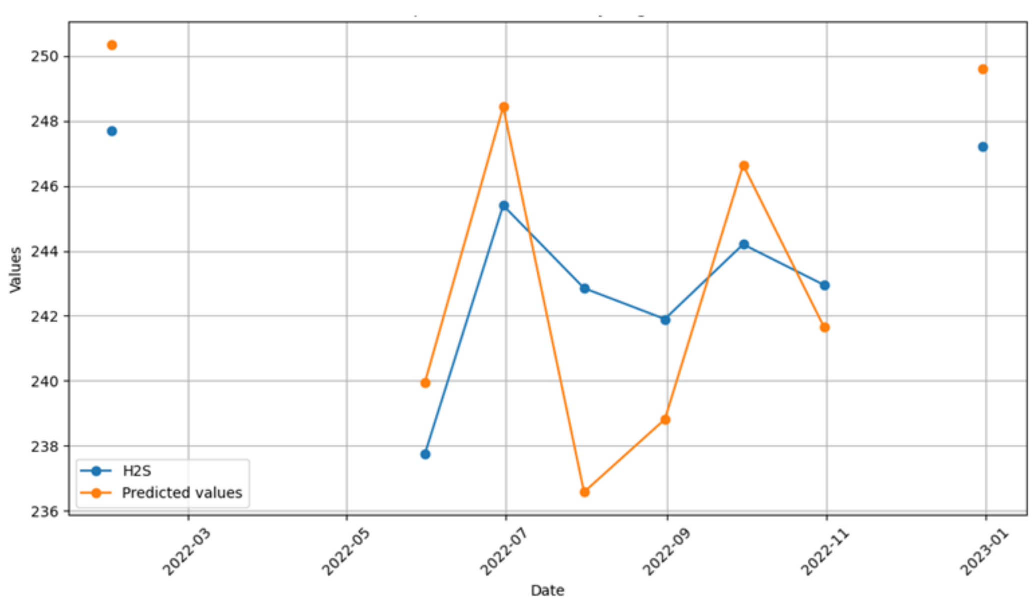


**Figure 10: Plot of observed and predicted values of hydrogen sulphidefor Oron.**

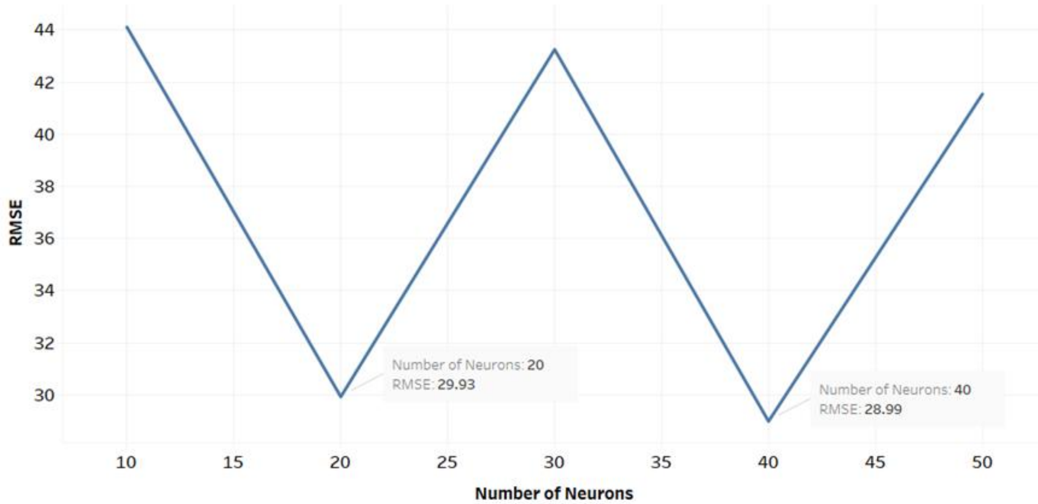


**Figure 11: Plot of hidden neurons and RMSE of ammoniafor Oron**

**Table 5: Hidden neurons and RMSE of ammoniafor Oron**

| Number of Neurons | RMSE |
|---|---|
| 10 | 44.11 |
| 20 | 29.93 |
| 30 | 43.25 |
| 40 | 28.99 |
| 50 | 41.54 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for ammoniaprediction are displayed in Table 5 and also plotted in Figure 11.

A line plot of the root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network is displayed in Figure 11. The graph demonstrates that when the hidden neurons were adjusted to forty (40), the neural network performed better. Therefore, 6-40-1 is the best model to predict ammonia for Oron. This equates to forty (40) hidden neurons in the neural network, one (1) goal variable—ammonia—and six (6) input variables—$PM_{10}$, $PM_{2.5}$, temperature, relative humidity, carbon dioxide, and hydrogen sulphide. Plotting the anticipated values from the neural network output against the actual ammonia values was done. The diagram is displayed in Figure 12:

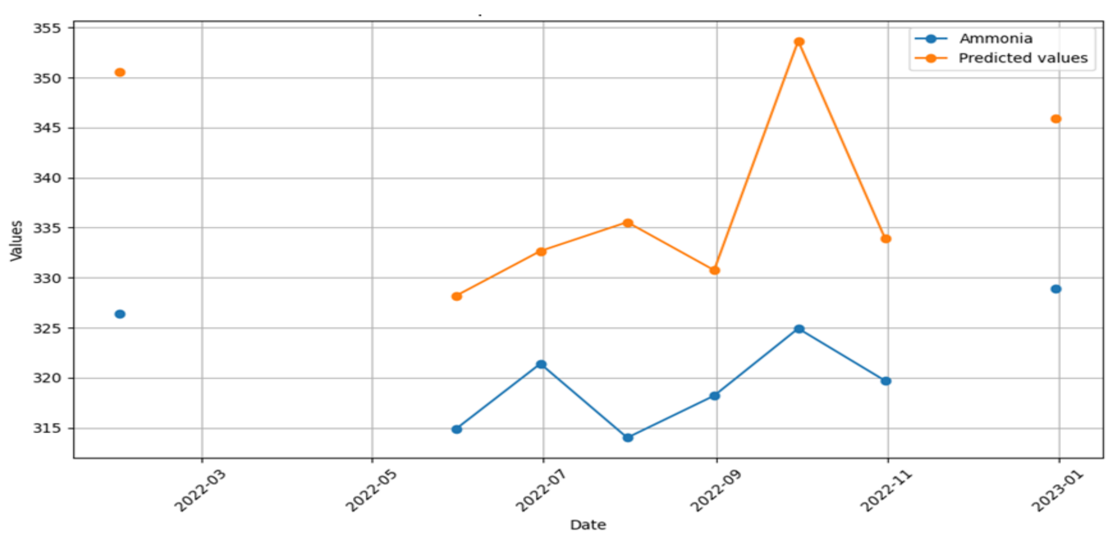


**Figure 12: Plot of observed and predicted values of ammoniafor Oron**

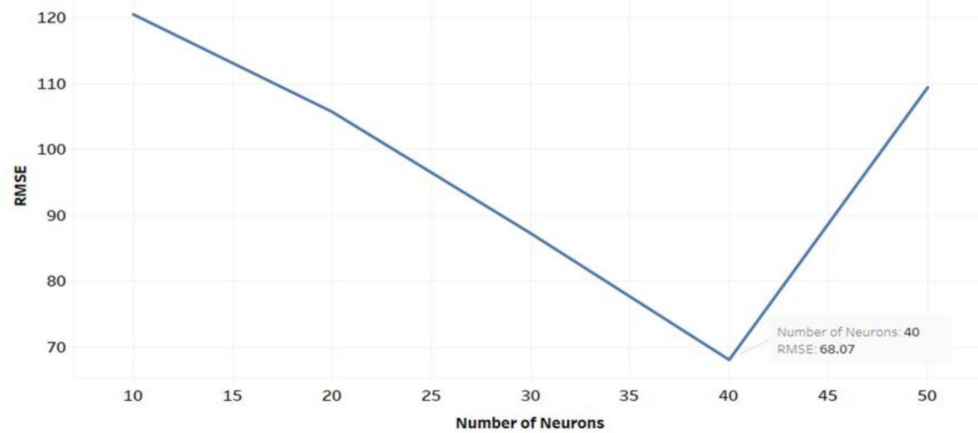


**Figure 13: Plot of hidden neurons and RMSE of $CO_2$ for Oron**

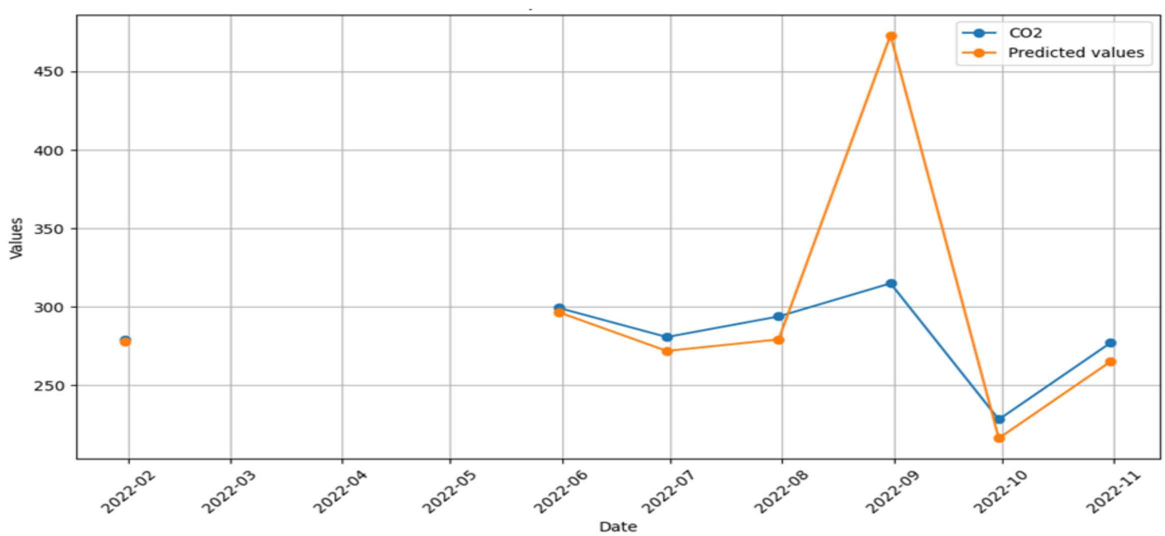


**Figure 14: Plot of observed and predicted values of $CO_2$ for Oron**

**Table 6: Hidden neurons and RMSE of $CO_2$ for Oron**

| Number of Neurons | RMSE |
|---|---|
| 10 | 120.53 |
| 20 | 105.75 |
| 30 | 87.29 |
| 40 | 68.07 |
| 50 | 109.45 |

The root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network for carbon dioxide ($CO_2$) prediction are displayed in Table 6 and also plotted in Figure 13.

A line plot of the root mean squared error (RMSE) and the quantity of hidden neurons utilized to train the network is displayed in Figure 13. The graph demonstrates that when the hidden neurons were adjusted to forty (40), the neural network performed better. Therefore, 6-40-1 is the best model to estimate carbon dioxide for Oron. This equates to forty (40) hidden neurons in the neural network, one (1) goal variable—carbon dioxide—and six (6) input variables—$PM_{10}$, temperature, relative humidity, $PM_{2.5}$, hydrogen sulphide, and ammonia. The anticipated values from the neural network's output were plotted against the actual carbon dioxide levels. The diagram is displayed in Figure 14:

## 4. Conclusion

In conclusion, this research has demonstrated the successful development and deployment of a novel multi-gas emission analyzer coupled with optimized Artificial Neural Network (ANN) models for predicting air quality parameters in the Oron Local Government Areas (LGAs) of AkwaIbom State. Thus, as a result of the collected data and proper analysis carried out, this study has provided valuable insights into the concentrations of various pollutants, including Methane, Ammonia, Hydrogen sulphide, Carbon dioxide, and Particulate Matters, across different locations within the study area.The accessibility and adaptability of these models empower stakeholders, including researchers, policymakers, and environmental scientists, to further investigate and address air quality concerns not only in Oron LGAs but also in similar settings by providing a comprehensive toolset towards achieving sustainable air quality objectives. This study, contributes significantly to the broader discourse on environmental management and pollution abatement initiatives in AkwaIbom State and beyond. Moving forward, continued collaboration and utilization of these innovative technologies and methodologies will be essential in fostering a healthier and more sustainable environment for present and future generations.

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