



Modelling and Analysis of Gaseous Pollutant Concentrations in Ughelli East Gas Plant

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Abstract

This study focused on the modelling and analysis of gaseous pollutant concentrations in Ughelli East gas plant located in Delta State, Nigeria. Aeroqual multi-parameter environmental monitor (series 500), was employed to monitor the concentrations of volatile organic compounds (VOCs), oxides of nitrogen (NO₂), oxides of sulphur (SO₂), ozone (O₃) and methane (CH₄). The concentrations of the particulate matter (PM_{2.5}) of these gases were obtained at each monitoring point on daily bases for a period of twelve weeks using Aerocet-531 SPM meter. Sky master thermo anemometer (SM-28) was used to obtain the important climatic variables (wind speed, atmospheric pressure, ambient temperature and relative humidity) which affect the dispersion of gaseous pollutants. The maximum concentration of each monitored gaseous pollutant during the twelve weeks monitoring period was selected and recorded for data processing. In this study, mathematical models were developed for predicting each gaseous pollutant such as volatile organic compounds (VOCs), oxides of nitrogen (NO₂), oxides of Sulphur (SO₂), ozone (O₃) and methane (CH₄). The curve fitting tool in Matrix Laboratory {MATLAB (2016a)} was employed to select models and to model the exact mathematical relationship between the pollutant concentrations and the flare distance; then the pollutants concentrations were predicted beyond the experimental distance of 500m from the flare point, the models were validated using coefficient of determination (R²), and root mean square error (RMSE). The results showed that R² ranges from 0.4916 to 0.9821, while the root mean square error (RMSE) ranges from 2.328 to 6.639. The results obtained from the validation showed good predictability and adequacy of the models developed.

1. Introduction

The amount of air inhaled per day is far more than the quantity of food and water consumed by human per day all put together [1]. Air pollution is the contamination of the atmosphere by gaseous, liquid or solid wastes or their by-products, including noise present in the atmosphere in concentrations that can endanger human health and the health and welfare of plants and animals, or can attack materials, reduce visibility, or produce undesirable odour. The products (pollutants) from burning of fossil fuels such as gas, oil, coal and wood affect the earth, buildings, water and air, resulting in fog, smog and global warming, which deteriorate vegetation, forests, and even human health [1,2, 3, 4]. Thousands of people in the world die each year due to heart and lung diseases that result from air pollution [5]. Air pollution which is any atmospheric condition in which certain substances (pollutants) are present in such concentrations that may produce undesirable effects on man and ecosystems, has become an extremely serious problem for the modern industrialized world

[6]. Within the Niger Delta area (especially ND Western Operation), is the Oil Mining Lease (OML) 34 comprising of Utorogu field and Ughelli East and West fields. The OML 34 field which is the case study area for this research work involves large scale combustion of gas by means of horizontal and vertical flares in Ughelli East. The consequential gaseous pollutants namely methane (CH_4), ammonia (NH_3), oxides of nitrogen (NO_2), particulate matters (PM), oxides of Sulphur (SO_2) and volatile organic compounds (VOCs) which are emitted from the flare sites are hazardous to man, animals and the total environment. Gaseous pollutants contamination in the Niger Delta area of Nigeria is a serious environmental concern for the entire area in particular and for Nigeria and the world in general since air pollution is never restricted to political boundaries. The increasing population and industrial growth as well as commercial operations in the Niger Delta area due mainly to oil and gas operations and processes brings to the fore the need for air pollution monitoring through assessment of pollutants concentrations, modelling of dispersion and prediction of pollutants spread, to help regulate and manage environmental impacts. Dispersion modelling is undertaken in order to predict the concentration and spread of pollutants [7]. Yannarwar et al [8] had the opinion that dispersion models are used to predict the fate of pollutants after they are released into the atmosphere. The goal of air quality dispersion modelling is to estimate a pollutant's concentration at a point downwind of one or more emission sources [9]. The first step in the modelling and prediction of ground level concentration of gaseous pollutants is to understand the exact mathematical relationship between the pollutant concentrations and the distance from flow station at normal environmental stability and wind speed.

This study therefore focused on the modelling and analysis of gaseous pollutant concentrations in Ughelli East gas plant.

2. Methodology

2.1 The study Area

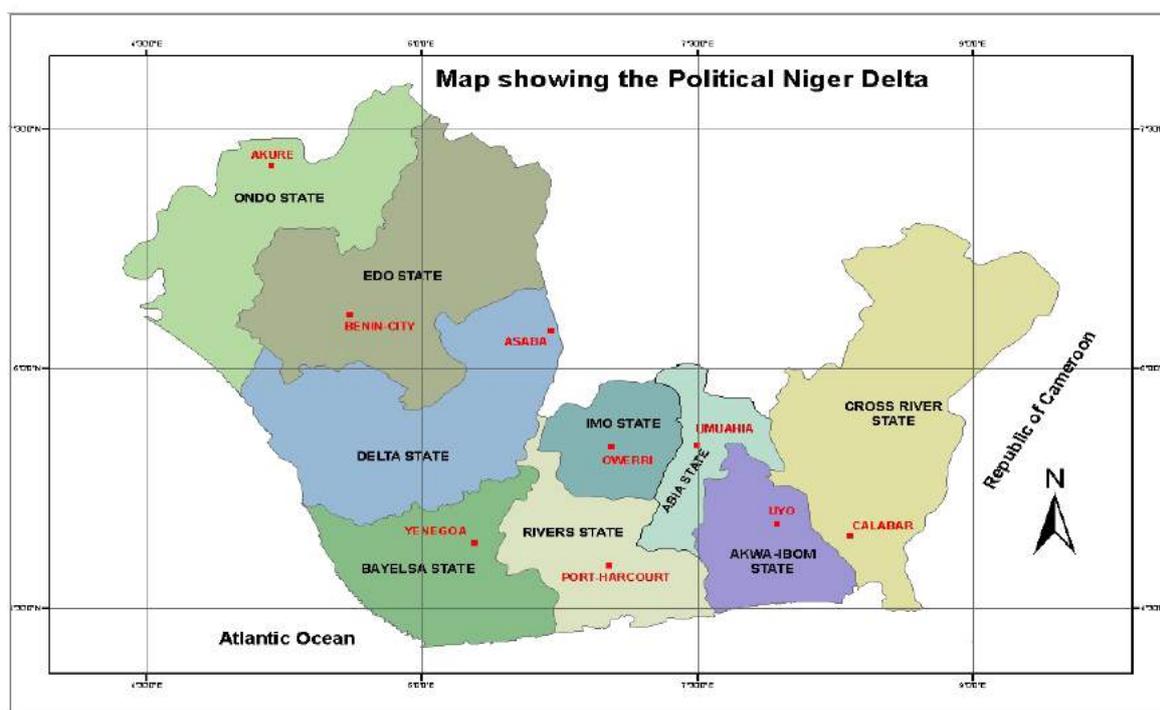


Figure 1: Political Map of Niger Delta of Nigeria [10]

Within the Niger Delta area, there are many natural gas processing plants which emit the common harmful gaseous pollutants into the atmosphere through continuous gas flaring. Example of such natural gas processing facilities for a case study in this research is the OML 34. The OML 34 (Oil Mining Lease 34) is located in the Western Niger Delta, and covers an area of about 950km². The producing fields is Ughelli East, with a total flow station capacity of 35mbpd. The Ughelli East facility is located at Ughelli North Local Government Area, in Delta State of Nigeria.

OML 34 is of utmost strategic importance to Nigeria and the West African sub-region, as a major supplier of gas for electricity generation in Nigeria. It also feeds gas through the West African Gas Pipeline (WAGP) to neighbouring countries [10].

Currently most of the exploration and production activities are focused within Ughelli East field. OML 34 is key to the nation's power generation. Gas from OML 34 is produced from its field, the Ughelli East field. The Ughelli East gas processing plant came on stream in 1966 with an installed capacity of 90mmscf/d. Six (6) NAG wells have been drilled to date in the field and the gas produced supplies the Transcorp Ughelli Power Station among others. Niger Delta Western is a major supplier of gas to the domestic market and the West African Sub-region which include Ghana, Lome and the Benin Republic via the West African Gas Pipeline [10, 11].



Figure 2: Map of Delta State Showing Position of OML34 in Ughelli East

2.2 Procedure

This study involves focused on the modelling and analysis of gaseous pollutant concentrations in Ughelli East gas plant from OML 34 in the Niger Delta area of Nigeria, was carried out using the following steps: -

1. Data acquisition and processing.
2. Computation of pollution standard index (PSI).
3. Simulation of environmental condition based on the computed PSI.
4. Geo-statistical analysis of the data
5. Modelling and Data analysis concentration of pollutants
6. Model validation.

2.2.1 Data Acquisition and Processing

In this study, six (6) gaseous pollutants namely; volatile organic compounds (VOCs), methane (CH₄), nitrogen dioxide (NO₂), particulate matter (PM_{2.5}), ozone (O₃) and sulphur dioxide (SO₂) were monitored on daily bases for a period of twelve (12) weeks and data were transformed into weekly maximum concentration. To select the maximum concentration of the pollutant at each sampling point within the entire period of experimentation for the modelling, extreme value statistics was carried out using the data analysis tool pack of Microsoft Excel 2010. The mandatory frequency of sampling for the gaseous point source emission monitoring was investigated on weekly basis and was found to be appropriate, a continuous emission monitoring system approved by the Director of Petroleum Resources (DPR) was utilized [10]. According to the descriptive statistics of data stated in Environmental Guidelines and Standards which stated that gaseous point sources emission monitoring shall be at distances of 200m intervals away from the installation along the direction of the prevailing wind [7]. Based on this and to determine the trend, the monitoring locations were established and the range of measurement was 60m to 500m away from the flare point at each station using a spacing distance of 60m, 80m, 100m, 150m, 200m, 250m, 300m, 350m, 400m, 450m and 500m from the flare point. Standard gaseous pollutants monitoring equipment used such as Gas monitor, SPM meter, Anemometer and GPS receiver were calibrated and used as follows. Aeroqual multi-parameter environmental monitor (series 500), having different gas sensors, was employed to monitor the concentration of volatile organic compounds (VOCs), oxides of nitrogen (NO₂), oxides of sulphur (SO₂), ozone (O₃) and methane (CH₄). The concentrations of these gases were obtained at monitoring location of Ughelli East flow station on daily bases for a period of twelve weeks. Aerocet-531 SPM meter was used to monitor the concentration of particulate matter (PM_{2.5}) at the location on daily bases for a period of twelve weeks. Sky master thermo anemometer (SM-28) was used to obtain the important climatic variables (wind speed, atmospheric pressure, ambient temperature and relative humidity) which affect the dispersion of gaseous pollutants. An updated map of the OML 34 was sourced from Shell Petroleum Development Corporation (SPDC), Delta State, Nigeria was used for this study. The Global Positioning System (GPS) receivers and point positioning techniques were used to obtain the geographical coordinates at each monitoring location in the study area. The coordinates were converted to decimal degrees format using the Universal Traverse Mercator (UTM) software version 1.0. The maximum concentration of each monitored pollutant during the twelve weeks monitoring period was selected and recorded for data processing. The data obtained in parts per million (ppm) were processed by converting the pollutants concentrations from ppm to mg/m³ or µg/m³, using the model presented below (Equation 1). This is because the pollutants hourly or daily or annually concentrations are measured in µg/m³ [10, 11].

$$\text{Concentration in mg/m}^3 \text{ or } \mu\text{g/m}^3 = \frac{\text{conc. (ppm)} \times \text{MW (g/mole)}}{\text{MV (L)}} \quad (1)$$

where:

Conc. = Concentration of pollutant

mg/m³ = milligram per cubic meter = 10⁻³g/m³

µg/m³ = microgram per cubic meter = 10⁻⁶g/m³

3. Results and Discussion

Table 1 shows the input parameter of the three flow stations presented to the neural network for validation of field data. The input parameters include; the sampling distance from flow station, wind speed, atmospheric pressure, ambient temperature and relative humidity. These parameters were selected because they form the critical climatic variables that affects the dispersion of gaseous pollutants.

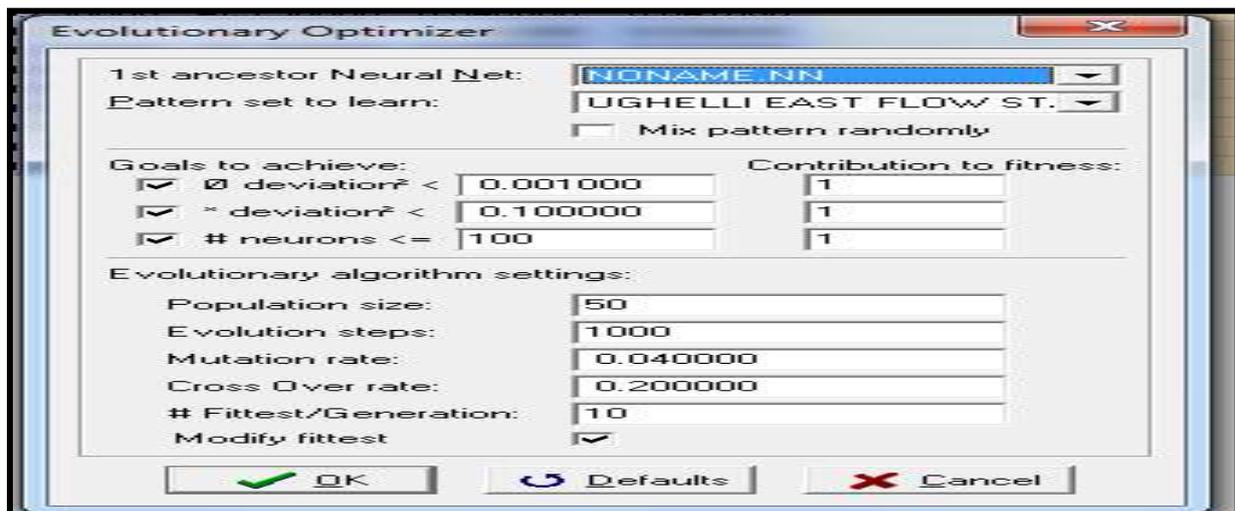
Table 1: Input Parameters for Ughelli East Flow Station

Sampling Distance (m)	Wind Speed (m/s)	Atm. Pressure (mmHg)	Ambient Temperature (deg C)	Relative Humidity (%)
60	3.89	1009	26.5	88.4
80	3.77	1009	22.7	91.8
100	3.81	1009	24.7	93.4
150	2.76	1009	23.4	83.5
200	2.82	1009	23.8	82.7
250	2.23	1009	26.1	88.9
300	1.71	1009	23.7	91.6
350	1.72	1009	24.8	93.3
400	1.91	1009	25.6	92.4
450	1.98	1009	25.7	89.1
500	2.11	1009	26.8	87.4

3.1 Validation of Field Data using Pythia (Neural Net Software)

The field data from the study locations were validated using artificial neural network designer software (Pythia). The field data were validated to evaluate the adequacy of the field data for use in air pollution modelling. The artificial neural network is trained to prevent it from memorizing data presented before it. Using the training data which is the field data collected, Pythia employed the evolutionary optimizer to search the neural network topology that best understand the input and output data presented for training, and the back propagation algorithm to produce the network. The reason for training is for the model to understand the data obtained and the condition under which they were obtained, so as to be able to make accurate correction. The criteria for selecting the best topology are the square of the deviation between the observed output and the predicted output coupled with the fitness accuracy. Topology with the least square deviation having 100% fitness was regarded as the best for the task. Pythia employs the back propagation algorithm to produce the network. During the training phase, the actual output of the network was compared with the experimental output and the error propagated back towards the input of the network. The network parameter which is the input is also called the “weight”.

Table 2: Condition for best performance



Based on the conditions of Table 2, the evolutionary optimization was performed to obtain the best neural network topology that best fits the input and output data for Ughelli East. The evolutionary optimization is presented in Table 2.

Table 3: Evolutionary Optimization for Selecting Best Network Topology

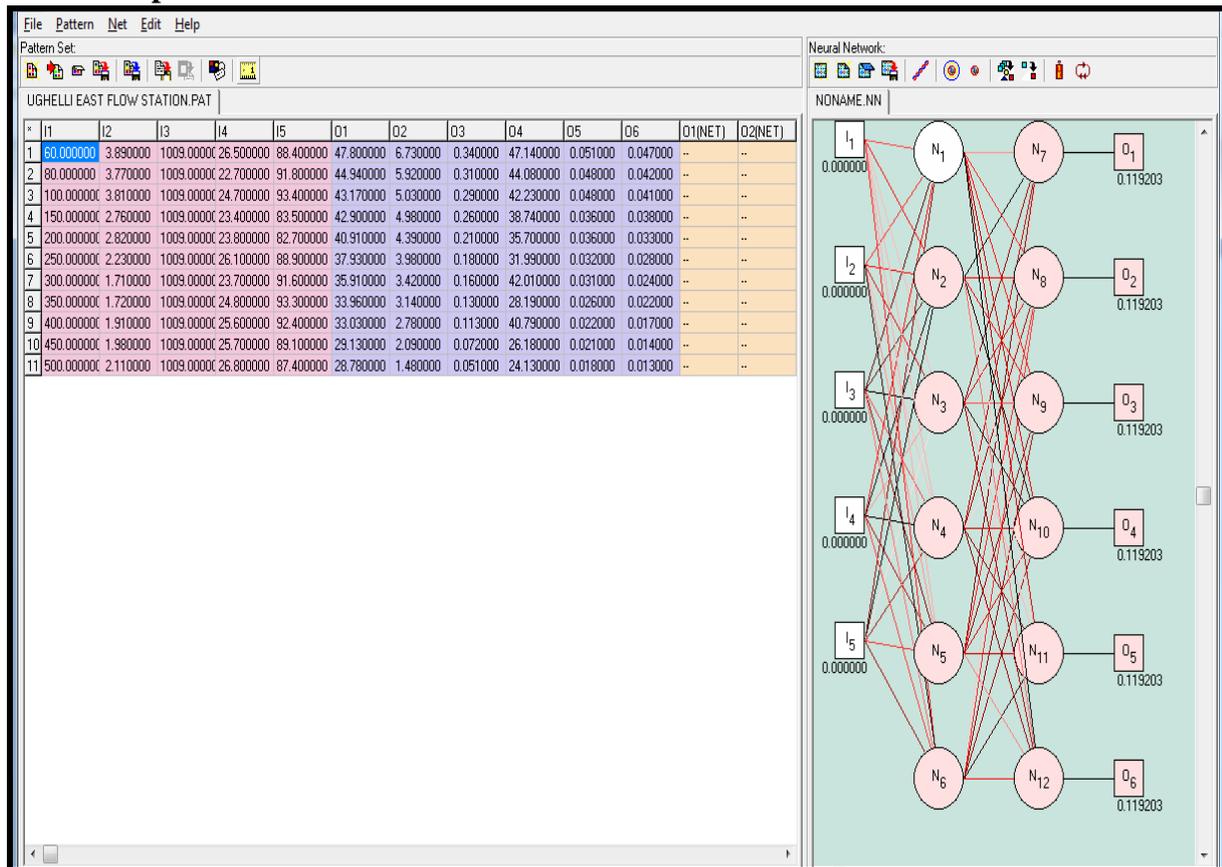
No	Topology	Neurons	Ø dev ²	* dev ²	Fitness
<input type="checkbox"/>	31 5,6,7,6,6,6	31	0.000305	0.000868	100.00000
<input type="checkbox"/>	32 5,6,6,6,6,6	30	0.000524	0.001431	100.00000
<input type="checkbox"/>	33 5,6,6,6,6,6	30	0.000479	0.000941	100.00000
<input type="checkbox"/>	34 5,6,6,6,6	24	0.000588	0.002221	100.00000
<input type="checkbox"/>	35 5,6,6,6	18	0.000765	0.002121	100.00000
<input type="checkbox"/>	36 5,6,5,6	17	0.001469	0.004796	89.36437
<input type="checkbox"/>	37 5,7,6	13	0.000805	0.001918	100.00000
<input type="checkbox"/>	38 5,6,6	12	0.002072	0.007394	82.75606
<input type="checkbox"/>	39 5,6,5,6	17	0.000609	0.001953	100.00000
<input type="checkbox"/>	40 5,6,6	12	0.001338	0.005047	91.58726
<input type="checkbox"/>	41 5,6,5,6	17	0.001399	0.004289	90.48680
<input type="checkbox"/>	42 5,5,5,5,6	21	0.000546	0.001897	100.00000
<input type="checkbox"/>	43 5,5,5,4,6	20	0.001216	0.004123	94.07202
<input type="checkbox"/>	44 5,5,5,4,4,6	24	0.000751	0.002169	100.00000
<input type="checkbox"/>	45 5,5,5,4,4,6	24	0.014059	0.141193	59.31273
<input type="checkbox"/>	46 5,5,4,3,6	18	0.001790	0.004660	85.29146
<input type="checkbox"/>	47 5,5,4,3,6	18	0.003841	0.011044	75.34487
<input type="checkbox"/>	48 5,4,3,6	13	0.003315	0.015837	76.72220
<input type="checkbox"/>	49 5,4,4,6	14	0.003555	0.015841	76.04195

Table 4: Evolutionary Optimization for Selecting Best Network Topology

No	Topology	Neurons	Ø dev ²	* dev ²	Fitness
<input type="checkbox"/>	0 5,6,6	12	0.005929	0.024995	72.28890
<input type="checkbox"/>	1 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	2 5,4,6	10	0.004683	0.022492	73.78423
<input type="checkbox"/>	3 5,5,6	11	0.001314	0.003404	92.02920
<input type="checkbox"/>	4 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	5 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	6 5,5,6	11	0.006203	0.040224	72.04079
<input type="checkbox"/>	7 5,5,6	11	0.004990	0.019950	73.34611
<input type="checkbox"/>	8 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	9 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	10 5,6,6	12	0.001408	0.004519	90.33391
<input type="checkbox"/>	11 5,6,6	12	0.003520	0.020675	76.13612
<input type="checkbox"/>	12 5,6,6	12	0.000750	0.002603	100.00000
<input type="checkbox"/>	13 5,6,6	12	0.003548	0.014210	76.06043
<input type="checkbox"/>	14 5,6,6	12	0.006397	0.038049	71.87771
<input type="checkbox"/>	15 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	16 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	17 5,6	6	0.011132	0.046365	69.66101
<input type="checkbox"/>	18 5,4,6	10	0.007250	0.029844	71.26415
<input type="checkbox"/>	19 5,6,3,6	15	0.004822	0.015597	73.57926

From Table 4, it was observed that a minimum of 12 neurons was needed to obtain an optimum topology of 5, 6, 6 having a fitness of 100% with a square deviation of 0.002603 for Ughelli East. Based on these parameters, optimum neural network architecture were produced as shown in Table 5.

Table 5: Optimum Neural Network Architecture



Using the network of Table 5, the Repro Pattern Set function of the Pythia program was then activated to predict the pollutants concentrations based on the input and output data from Ughelli East flow stations. Reliability plots of the field data and the ANN predicted data were obtained to test the correlation between the field data and the ANN predicted data.

3.2 Sensitivity analysis of ANN

A sensitivity analysis was performed to allow the network assign weight to each input variable on the bases of their significant contribution so as to determine the input parameter that contributes mostly to variation in the pollutant concentrations around the study locations.

3.3 Selection of Trend Analysis Model using Normality Test

In order to check the distribution of the field data, normality test was also employed to select the most appropriate model for trend detection and estimation. If data are linearly distributed then parametric model (linear regression model) such as least square linear regression will be most appropriate for trend detection and estimation otherwise non-parametric model such as Mann-Kendall and Thiel Sen's slope estimation will be employed for detection and estimation of trend in the data. To test if the field data followed a normal distribution, histogram plot and normal Q-Q plot was employed. For normality, the histogram must be assumed to have a bell shape configuration and the data points on the normal Q-Q plot must follow the 45° center line else it will be concluded that the data are not normally distributed. Consequently, non-parametric analysis will be needed to determine the occurrence of trend in the data [5]. The practical implication of trend detection is to know exactly what is happening around the study location.

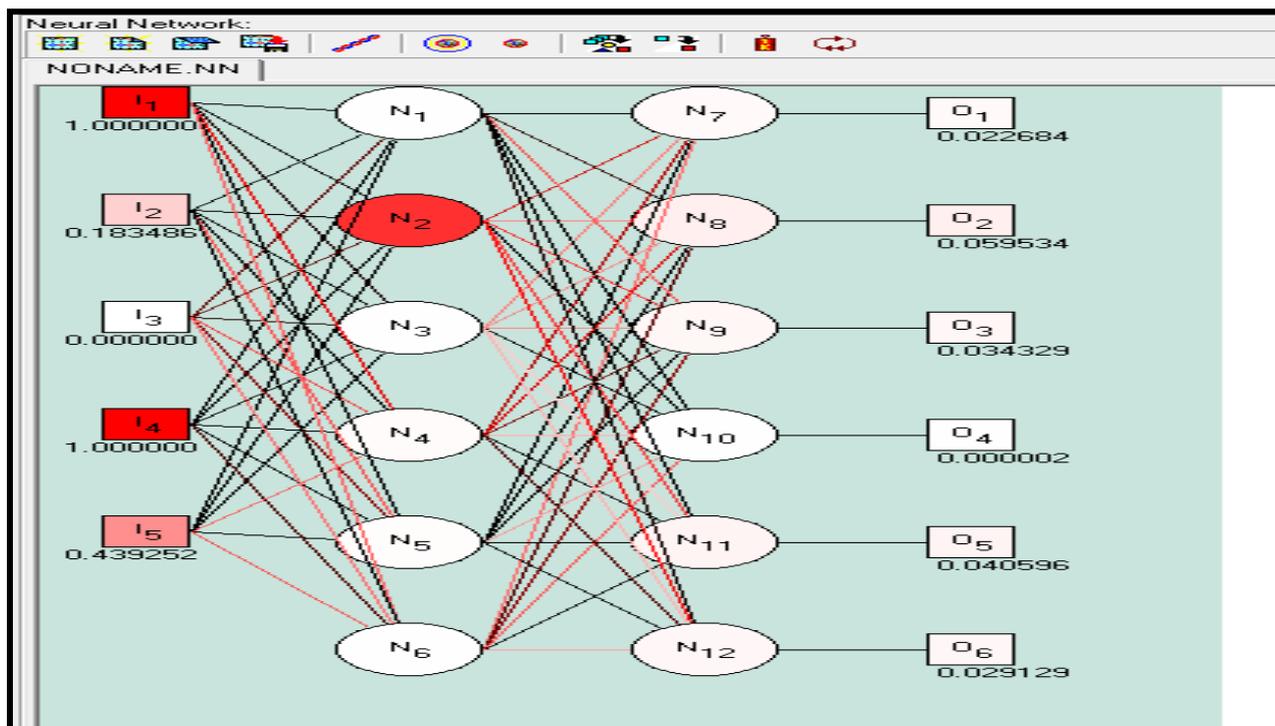


Figure 3: Sensitivity Analysis of ANN (Ughelli East)

Table 6: Calculated model parameters for VOC (Ughelli East)

Model	R-Square	Adj. R-Square	SSE	RMSE
Linear polynomial	0.9813	0.9793	7.699	0.9249
Quadratic Polynomial	0.9824	0.9780	7.259	0.9526
Exponential	0.9815	0.9794	7.648	0.9218
Gaussian	0.9824	0.9780	7.273	0.9535
Fourier	0.9824	0.9749	7.259	1.018

Based on the parameters of Table 6, it was observed that the quadratic polynomial model had the lowest error sum of square value of 7.259 and coefficient of determination R^2 value of 0.9824.

Table 7: Quadratic polynomial function for VOCs versus sampling distance

```

Linear model Poly2:
  f(x) = p1*x^2 + p2*x + p3
Coefficients (with 95% confidence bounds):
  p1 = 1.15e-005 (-2.658e-005, 4.958e-005)
  p2 = -0.04758 (-0.0687, -0.02646)
  p3 = 49.31 (46.93, 51.69)
    
```

where;

$f(x)$: VOCs concentration ($\mu\text{g}/\text{m}^3$)

x : Sampling distance (m)

Using the quadratic polynomial function of Table 7, the concentration of VOCs was projected to a sampling distance of 1500m at 95% confidence level.

Table 8: Calculated Model Parameters for PM_{2.5} (Ughelli East)

Model	R-Square	Adj. R-Square	SSE	RMSE
Linear polynomial	0.6176	0.5751	232.1	5.078
Quadratic Polynomial	0.6176	0.5220	232.1	5.386
Exponential	0.6159	0.5733	233.1	5.089
Gaussian (Gauss 3)	0.9821	0.9107	10.84	2.328
Fourier	0.4916	0.2736	308.5	6.639

Based on the parameters of Table 8, it was observed that the Gaussian model had the lowest error sum of square value of 10.84 and coefficient of determination R² value of 0.9821.

Table 9: Gaussian Model for PM_{2.5} versus Sampling Distance

```

General model Gauss3:
  f(x) =
          a1*exp(-(x-b1)/c1)^2) + a2*exp(-(x-b2)/c2)^2) +
          a3*exp(-(x-b3)/c3)^2)
Coefficients (with 95% confidence bounds):
a1 =      1591   (-3.061e+005, 3.093e+005)
b1 =     -4647   (-2.489e+005, 2.396e+005)
c1 =      2494   (-5.929e+004, 6.428e+004)
a2 =  3.722e+004  (-2.478e+020, 2.478e+020)
b2 =      314.8  (-7.211e+015, 7.211e+015)
c2 =      5.174  (-4.319e+015, 4.319e+015)
a3 =      124.9  (-1.834e+011, 1.834e+011)
b3 =       421  (-1.962e+009, 1.962e+009)
c3 =       14.25 (-3.489e+009, 3.489e+009)
    
```

where;

f(x): particulate matter concentration (µg/m³)

x: Sampling distance (m)

Using the Gaussian model of Table 9, the concentration of particulate matter was projected to a sampling distance of 1500m at 95% confidence level.

3.4 Analysis of Seasonal Variability using Autocorrelation Function

Accurate analysis of data collected over time requires that seasonality analysis to check for the presence of seasonal variability be performed [6]. To estimate the degree of seasonality present in the field data collected from the three flow stations, autocorrelation plot was employed. A statistical software EViews version 9.0 was employed to generate the correlogram.

3.5 Trend Estimation using Non Parametric Analysis

Since it was established that the field data collected from Ughelli East flow station and Ughelli West flow station are not normally distributed by exhibiting some characteristics that is occasioned by the presence of trend and seasonal variability, then non parametric analysis became the most suitable method to estimate the presence of trend in the data. Mann- Kendall trend test was therefore carried out by plotting the pollutants concentration against generated index.

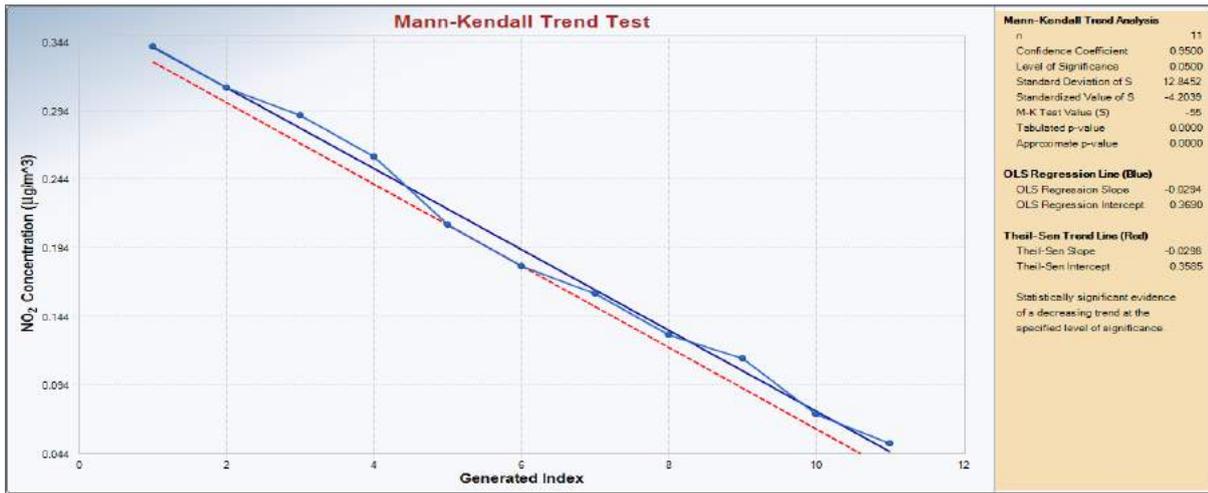


Figure 4: Mann-Kendall Trend Test of VOCs Data from Ughelli East Flow Station

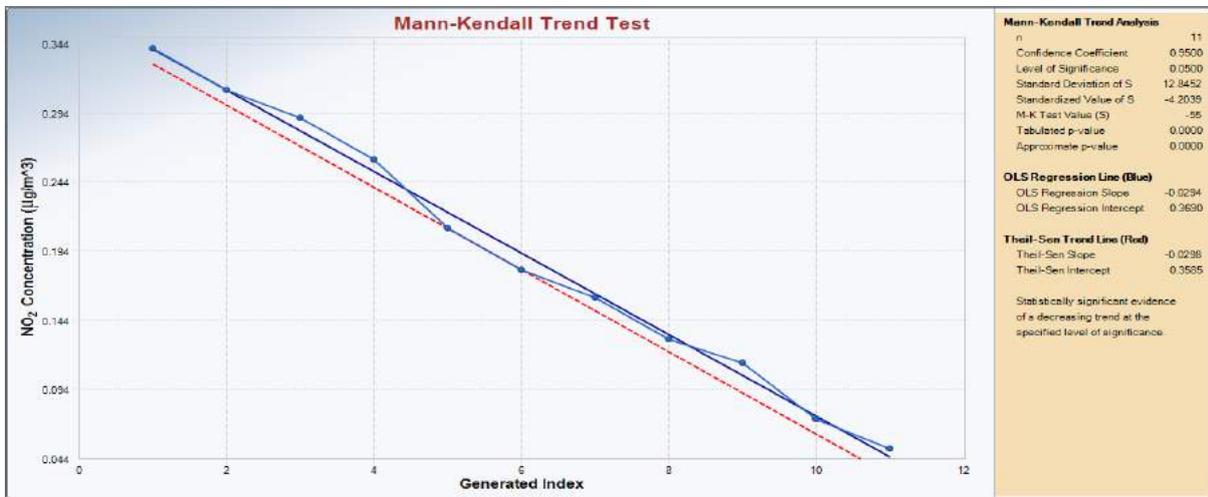


Figure 5: Mann-Kendall trend Test of NO₂ Data from Ughelli East Flow Station

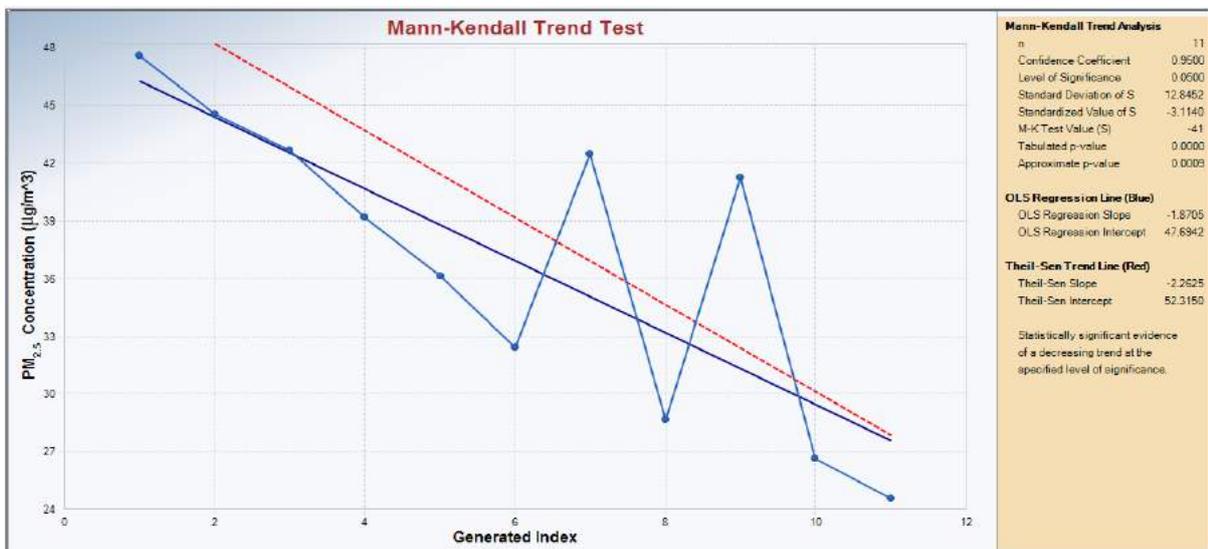


Figure 6: Mann-Kendall Trend Test of PM_{2.5} Data from Ughelli East Flow Station

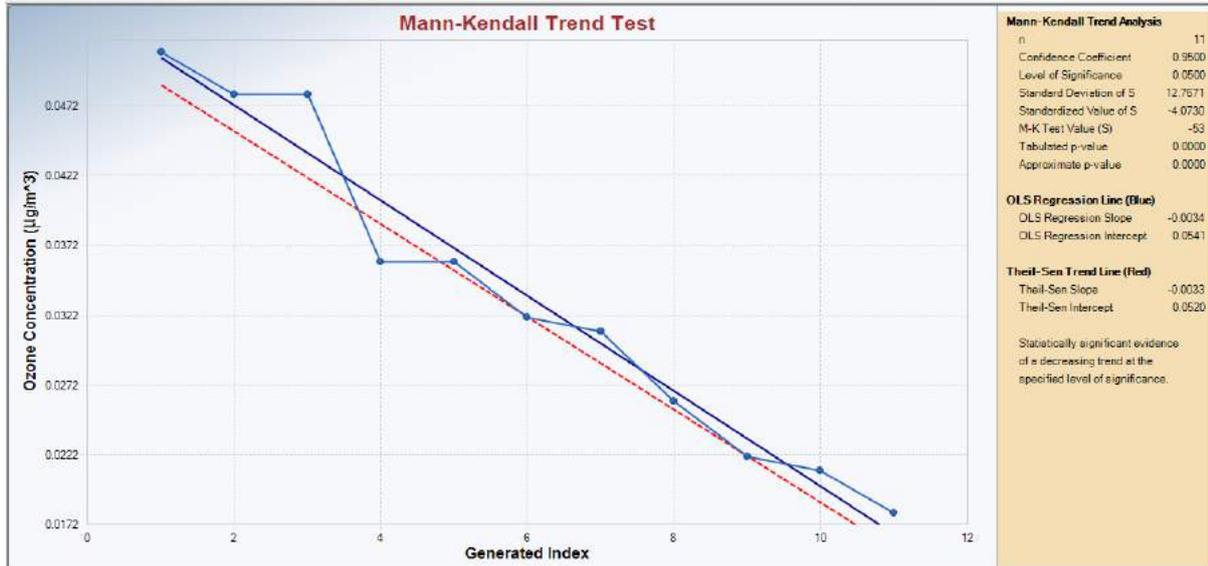


Figure 7: Mann-Kendall Trend Test of Ozone Data from Ughelli East Flow Station

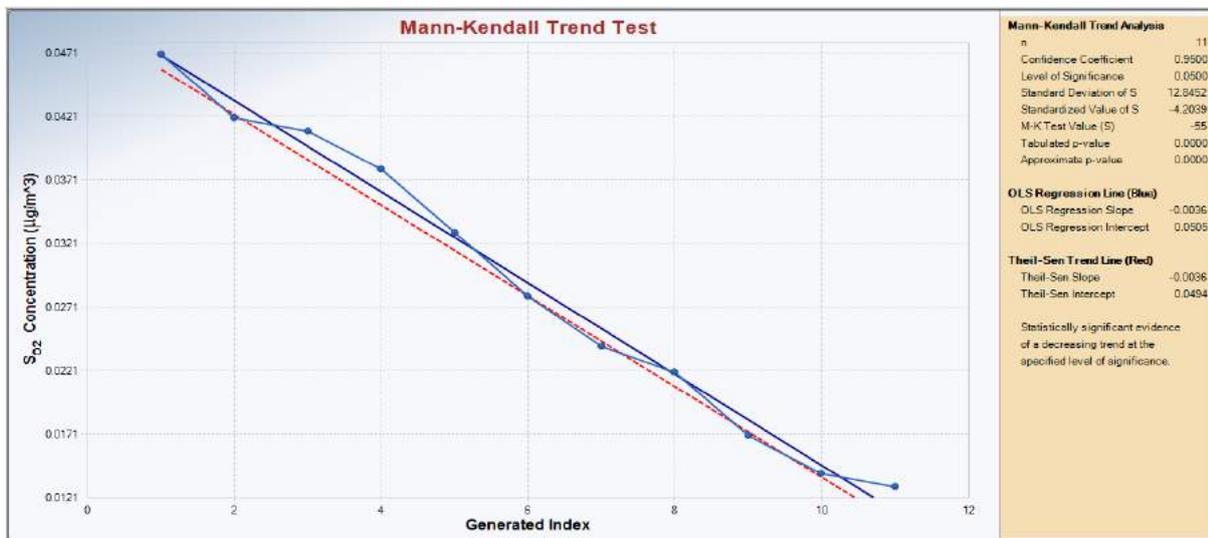


Figure 8: Mann-Kendall Trend Test of SO₂ Data from Ughelli East Flow Station

3.6 Geo-statistical Analysis of the Data

Detailed geo-statistical analysis of the data acquired from the three locations was carried out using ArcGIS 10.4.1. Geospatial modelling was employed to generate the prediction maps which show the distribution of the pollutants around the study locations. The prediction map is a pictorial presentation of the pollutant concentrations in space. The input parameters for the modelling were the rectangular coordinates of each sampling point and the concentration of the different pollutants measured, namely: volatile organic compounds (VOCs), methane (CH₄), nitrogen dioxide (NO₂), particulate matter (PM_{2.5}), ozone (O₃) and Sulphur dioxide (SO₂). Several geostatistical methods exist for geospatial modelling but the kriging method for point source pollution was employed.

3.7 Network Testing/Validation

Cross validation data representing 25% of the total input data was introduced to monitor the training process and to prevent the network from memorizing the input data while the remaining 15% was employed to test the performance of the trained network [3].

Table 10: Ughelli East Network Testing using Different Sets of Input Parameters

Sampling Distance (m)	Wind Speed (m/s)	Atm. Pressure (mmHg)	Ambient Temperature (deg C)	Relative Humidity (%)	PM _{2.5}
600	3.44	1255	31.4	89.6	21.15206
650	3.76	1023	32.3	87.3	21.19357
700	4.89	1015	33.8	99.2	26.11066
750	5.6	1116	28.2	94.2	16.15206
800	4.33	1222	29.7	83.8	25.65206
850	6.43	1033	34.8	90.1	21.15237
900	5.89	1035	36.3	75.4	21.15252
950	2.33	1010	31.8	78.8	15.23341
1000	4.44	1056	30.9	88.2	18.65206

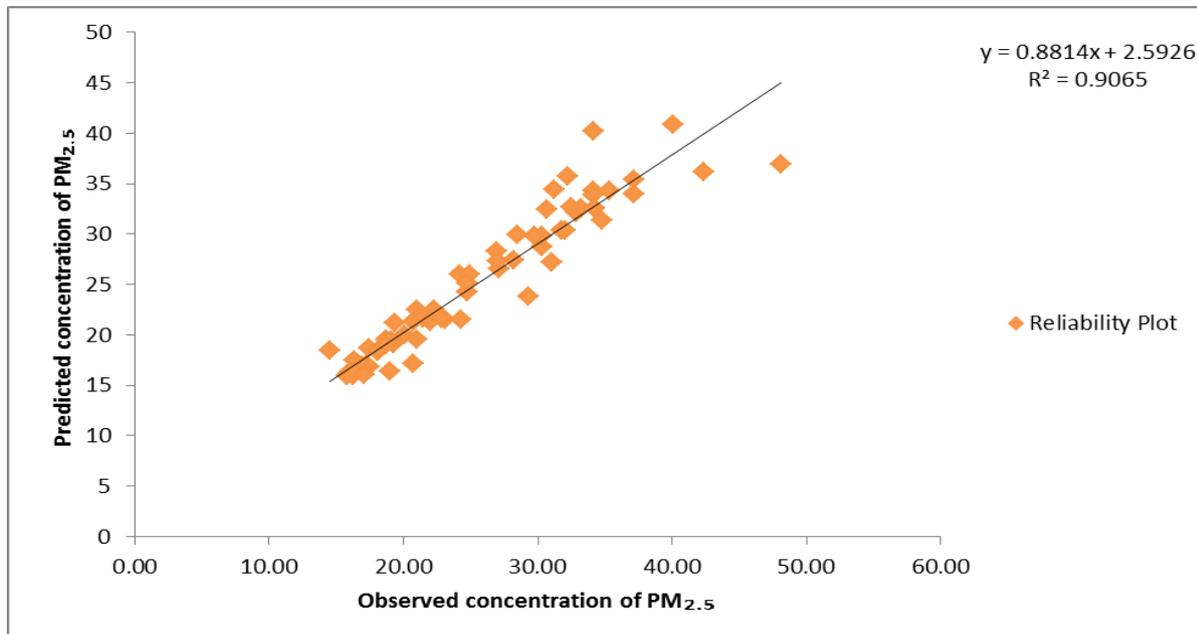


Figure 9: Regression plot of observed versus predicted concentration of PM_{2.5}

Based on the calculated coefficient of determination (R^2) as observed in Figure 9, the trained network was then employed to predict the concentration of PM_{2.5} around Ughelli East flow station as presented in Table 8.

4. Conclusion

The modelling and analysis of gaseous pollutant concentrations in Ughelli East gas plant had been achieved. Based on the computed values of the correlation coefficient (R) as observed, it was concluded that the network has been accurately trained and can be employed to predict the concentration of PM_{2.5} beyond the sampling distance. To certify the adequacy of the field data, neural network designer software (pythia) was employed to validate the data and the result revealed that the data were adequate for use. From the results of all the analysis and modelling done on the field data, it was observed that the computed error values associated with the non-linear

mathematical model namely: quadratic polynomial, exponential model, Fourier function and Gaussian model were observed to be less than that of linear polynomial model, it was concluded that the non-linear mathematical models were the best fit models to accurately describe the exact mathematical relationship between the concentrations of the gaseous pollutants and the sampling distance.

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