IJNRD.ORG ISSN : 2456-4184

International Research Journal
IJNRD
Research Through Innovation

INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

MODELLING THE RELATIONSHIP BETWEEN AIR POLLANTS AND METEOROLOGICAL VARIABLES; A CASE STUDY OF ALESA-ELEME, RIVER STATE, NIGERIA

[1]Ahmad K, [2]Leton T. G & [2]Ugbebor J. N.
[1,2 &3]Center for Occupational Health and Safety, Institute of Petroleum Studies, University of Port Harcourt, Nigeria.

Abstract

This study was aimed at developing a predictive model based on relationship between air pollutant and meteorological parameters using hourly and daily air pollutants (VOC, CO, PM$_1$) and meteorological parameters (Wind Speed, Air temperature, Solar Radiation, Rain fall) data from Alesa-Eleme, River State for a period of fourteen (14) months. The data was gathered using AQM 65 (Monitoring Station) strategically located at three (3) sites, in real time, spread over the study area. The was analyzed using descriptive, correlation and regression analysis., The results revealed that; at Station A, CO has weak and direct relationship with air temperature and Solar radiation, and weak and inverse (negative) relationship with wind direction and rain. VOC has weak and direct relationship with air temperature, solar radiation and rain, and weak and inverse relationship with wind direction. then PM has strong and direct relationship with air temperature and solar radiation but inverse and weak relationship with wind direction and rain. At station B, CO had strong and direct relationship with air temperature and weak and direct relationship with Solar radiation, and weak and inverse relationship with wind direction and rain. VOC had weak and inverse relationship with wind direction air temperature, solar radiation and weak and direct relationship with rain while PM$_1$ has strong and direct (positive0 relationship with air temperature and solar radiation, weak and direct relationship with wind direction but inverse and weak relationship with rain. Finally at station C, CO has weak and direct relationship with air temperature and Solar radiation, and weak and inverse relationship with wind direction and rain. VOC was weakly and inversely related to wind direction and solar radiation, weakly and directly related to rain and strongly and inversely related to air temperature while PM was strongly and direct related with air temperature and solar radiation, weakly and directly associated with wind direction but inversely and weakly associated with rain. The model for CO and PM were significant while that of VOC was not developed because it was not significant.

INTRODUCTION

Rising illness and mortality rates have been linked to air pollution, making it a particularly baffling environmental problem in both developed and developing nations (Barman et al., 2012). Quite a few activities can contribute to air pollution. Smoke, dust, fumes, aerosols, and radioactive materials are all examples of air pollutants (Tawari and Tawari, 2012). There is now the need to have safe level of exposure to air pollutants in the modern world, especially in the urban centers of most developing nations. While there are some natural contributors to air pollution, the great bulk of the problem can be traced to human activity. This is because, in their quest for a better quality of life, people have rapidly industrialized and urbanized, leading to the emission of numerous air pollutants. Air pollution continues to generate a lot of attention across the world because of the harm it does to people's health and welfare. Hypertension and other cardiovascular disorders are some of the health problems associated to the exposure of polluted air (Sanjay, 2008).

In many cities throughout the world, air pollution has become a serious problem because of these and other impacts. According to the World Health Organization (2019), air pollution is the most serious environmental risk, and this fact is being exploited to motivate sustainable development efforts. At least $5 trillion in lost wealth and $225 billion in lost productivity have been attributed to air pollution across the globe (World Bank, 2016). Premature mortality from cardiovascular disease, chronic obstructive pulmonary disease, lung cancer, and acute respiratory infection account for around seven (7) million fatalities annually due to air pollution.

Air pollution has been linked to an increase in disease rates in Rivers State, according to research by Nwachukwu et al. (2012). Diseases like pertussis, pulmonary tuberculosis, cerebrospinal meningitis (CSM), pneumonia, measles, chronic bronchitis, and upper respiratory tract infections (URTI) were prevalent in the study area because air pollutants concentration was above National and International (WHO) ambient air quality set limits. The results of the study are based on a comparison between air quality statistics from the World Health Organization and information on the prevalence of specific diseases obtained from the Ministry of Health, which therefore, suggest that Real-time air quality data is required to support this conclusion. According to research conducted in Orlu (Imo State, Nigeria) (Francis Ch et al., 2017), certain important air pollutants (PM$_{10}$, NO$_2$, and CO) have concentrations that exceed the National Ambient Air Quality (NAAQ) Standards, particularly in the afternoon (commercially active period). Data for the study was collected once a week for three months using a backpack-mounted air quality monitor. Therefore, it is evident that real-time continuous air pollution data is required that takes into consideration time and meteorological variations which affect concentration of air pollutants.

Combustion of fossil fuels like coal and gasoline releases harmful pollutants into the atmosphere that must be constantly monitored to ensure safe levels of exposure for humans. These pollutants include nitrogen dioxide (NO_2), sulphur dioxide (SO_2), volatile organic compounds (VOC), carbon monoxide (CO), and particulate matters ($PM_{2.5}$, and PM_{10}). In Nigeria, the Niger Delta region is the epicentre of Nigeria's oil and gas industry, and as such, it is also the region with the highest concentration of air pollutants such as particulate matter ($PM_{2.5}$ and PM_{10}), carbon dioxide (CO_2), sulphur oxide (SO_x), and nitrogen oxide (NO_x) (Zabbey et al., 2021).

Petroleum production, refining, petrochemical and gas processing industries are suspects of significant contribution to air pollution (Jerievi et al., 2019). Knowledge of the air quality baseline in the area around these industries is very essential in understanding air pollution and development of management plan. Unfortunately, we cannot get this data since stringent air pollution restrictions were not in place when most of these activities were established. However, if the refinery in Port Harcourt were to be on shut down mode for more than six (6) months, baseline data on air quality could be generated which will help in better understanding and management of air pollution. This forms the bases of this research work.

Air quality around industrial facilities or an area prone to air pollution from industrial and other human activities needs to be monitored on a continuous long-term basis (Al-Salem and Khan, 2008; Simpson et al., 2013; Sanchez et al., 2019). Current air quality reports suggest further study is needed to better understand the complex relationship between ambient air quality measures before any pollutant may be forecasted using information about another pollutant. Novel approaches that incorporate state-of-the art technology deployment to study air pollutants concentrations and the level of association/relationship among pollutants and with meteorological variables will accelerate air pollution studies and management. In this research, real-time air quality and metrological data ewre generated, and regression analysis was deployed to develop mathematical models for predicting concentration of air pollutants, understanding the relationship among air pollutants and their dispersion/conversion as affected by meteorological variables and seasonal variations. This is aimed at improving our understanding and management of air pollution issues in the study area and other locations with comparable characteristics.

AIM OF THE STUDY

The aim of this study is to collect and analyses meteorological and air pollutants data in the study area, determine how the two are related through the correlation, and then generate a mathematical model for forecasting purposes for better understanding and management of air pollution.

RESEARCH METHODOLOGY

3.1 Study area,

The study area (Port Harcourt Refining Company Ltd, complex) is located at Alesa-Eleme (4°45'33"N 7°06'15"E), Port Harcourt Rivers State, Nigeria. Major activity in the study area is petroleum refining. Although power plan and utilities like wastewater treatment plant were partially on stream, the process plants were on shut down mode (due to operational issues) during the study period. The power plant has four (4) gas turbine generators with 24 MW capacity each but only one was running to maintain the power requirement during shutdown. The wastewater treatment plant was designed to treat 16 m^3 of sanitary wastewater and 495.6 m^3 of combined process wastewater. However, only sanitary wastewater (3.13% of the wastewater treatment capacity) is being treated during the study period due to process plants being on shut down mode. These created an environment that support the conduct of base line air quality studies in the area. Figure 3.1 shows the google snapshot of the study area and location of air quality/weather monitoring stations.

The three (3) monitoring stations (AQM 65 – Air pollutants and weather monitors) were sited in accordance with special attributes and scale with reference to recommended standards. For ease of identification and reference, the monitoring Stations were labelled as Station A (4°45'33"N 7°06'32"E), Station B (4°45'21"N 7°06'07"E) and Station C (4°45'56"N 7°06'03"E). Station A is about 334.44 m downwind of the gas turbines, 145.59 m downwind of steam boilers stack, 242.06 m downwind of process plants and 374.49 m away from flare stack (96 m height). Station B is about 125.29 m downwind of wastewater treatment plant, 30.76 m in proximity to oily/observation ponds and 1,192.94 m away from flare stack. Station C is about 106.59 m downwind of another process plant and 1,161.3 m away from flare stack. These mean that, Station A will have pollutants majorly from gas turbine, Station B will have pollutants majorly from wastewater treatment plant while Station C will have background pollutants considering the shutdown mode of the refinery.

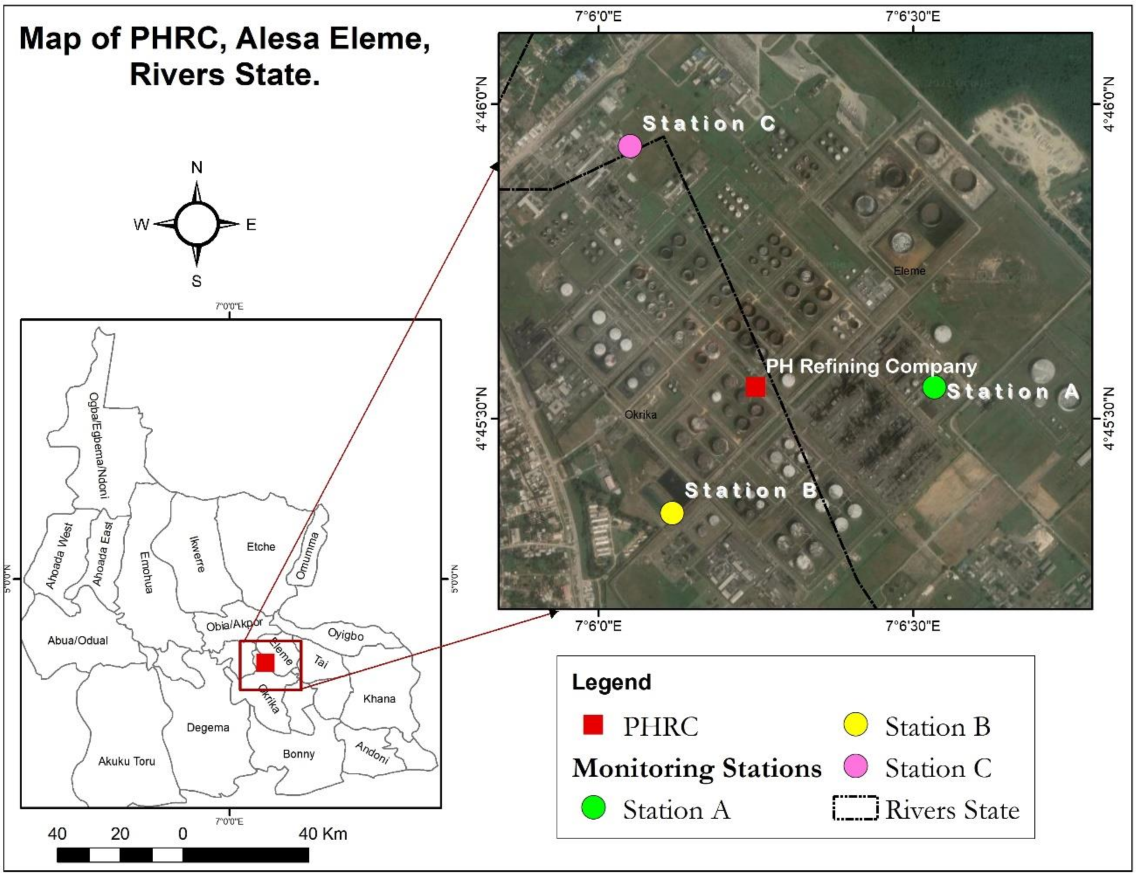

Figure Error! No text of specified style in document..**1: Google Snapshot of the Study Area**

3.2 Study Design

Three (3) air quality and weather monitoring stations (AQM 65) were sited at different locations within the study area in accordance with specio-temporal consideration. Air pollutants and meteorological data were collected using AQM 65 in accordance with manufacturer's recommendations. The air sample collected via gas and particulate matter inlets of the AQM 65 were analysed by the different modules located in the equipment cabin. To ensure consistency of data, descriptive statistics was applied for air pollutants and meteorological data as well as correlation matrix between the pollutants considered. Correlated parameters were additionally regressed to generate mathematical models for future predictions of air pollutants concentration.

3.3 Sample and Sampling Technique

Air Quality Monitor 65 (AQM 65) is an outdoor weather-proof integrated monitoring station that measures up to 20 gaseous air pollutants, particulate matter, and meteorological parameters simultaneously and continuously. Diagram describing AQM 65 is presented in Figure 3.2. Three (3) AQM 65 stations were strategically located at different monitoring locations as described in the study area above. Air sample is being drown through the inlet port by a suction pump. The air moves through a Teflon tube into various network of modules where the air is being analyzed and concentration of pollutants measured before it is expelled out through the exhaust port.

To ensure consistency of sampling within the breathing zone and allow for data comparison among the three (3) monitoring stations, a height (above the ground level) of 1.8 m for gas inlet, 2.1 m for particulate matter inlet, 2.1 m for weather station and 1.7 m for solar meter was selected and adopted (AS/NZS 3580.1:2016).

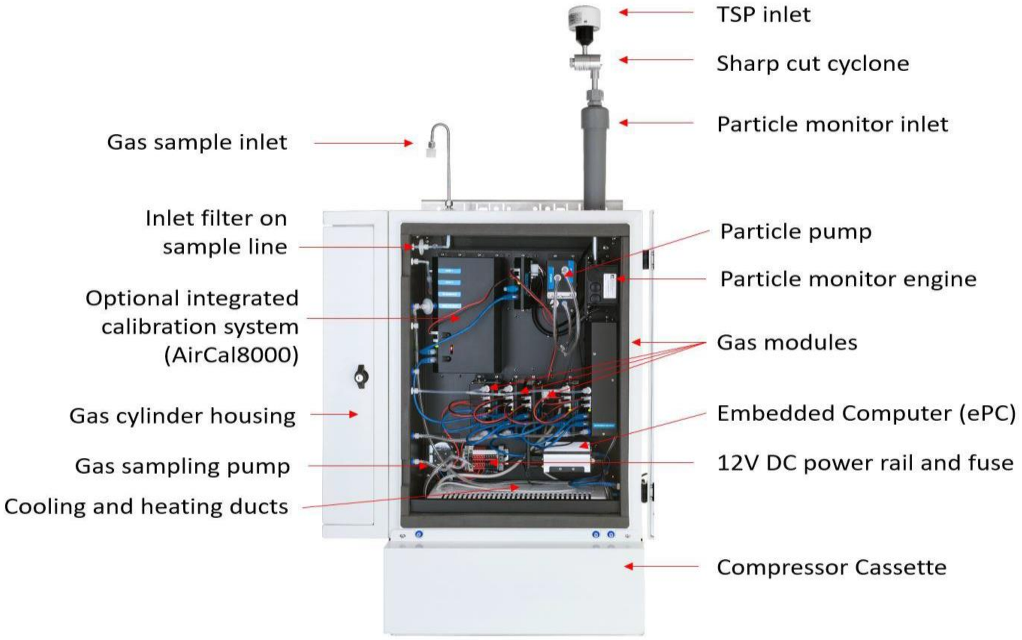

Figure Error! No text of specified style in document..**2: Description of AQM 65**

3.4 Method of Data Collection

The air sample collected from the AQM 65's gas and particulate matter inlets was analyzed by all of the modules housed in the equipment cabin. Modules determine CO, VOC, and PM_1, concentrations, stores and transmit data via cloud plus interface. The AQM 65 monitoring station had Vaisala weather meters for measuring wind speed, temperature, and precipitation, as well as a pyranometer for measuring sola radiation. Three (3) monitoring stations collected the data, which was subsequently sent to cloud plus and downloaded for analysis. All three (3) AQM 65 monitoring stations were calibrated on 07/08/2019 using NIST and ISO traceable test method 9722-1-6100 (ISO).

3.5 Method of Data Analysis

There were three methods used to assess the gathered data on air quality and meteorology in this study. At the initial step, meteorological and contaminant data were subjected to descriptive statistics. Subsequently, air pollutant and weather data from October 2019 through January 2021 were analyzed using the Spearman correlation approach and a correlation matrix, that includes all of the parameters in question was generated. Third, the relationship between weather conditions and their associated pollutants was analyzed to create mathematical models for prediction at minimal cost and time.

4. RESULTS AND DISCUSSION

4.1 Descriptive Analysis Results of Daily Average Air Pollution and Meteorological Parameters

In this study, the air pollution data was obtained from the monitoring Stations (A, B & C) in the study area (STATION A (4º45'33"N 7º06'32"E), STATION B (4º45'21"N 7º06'07"E) and STATION C (4º45'56"N 7º06'03"E) for a period of fourteen months (November 2019 – January 2021) which was recorded as daily and hourly concentration of Particulate Matter (PM_1,), CO (Carbon monoxide) and volatile organic compounds (VOC). Daily and hourly meteorological data including wind speed, (WS) air temperature, solar radiation and rainfall for the same period was also collected. The data was pre-processed using exponential data smoothing (because of high correlation between the pre-processed and the raw experimental data) in time-series via XLSTAT add-in in MS Excel 2019 application. After smoothening, the data was organized, processed and presented as mean, standard deviation, skewness, minimum and maximum values in Table 4.1- 4.3 below.

Table Error! No text of specified style in document.**.1: Descriptive statistics of daily air pollutants and meteorological parameters obtained from STATION A**

Parameter	Unit	Mean	St. Dev.	Skewness	Range	Min.	Max.
CO	Ppm	0.5635	0.2388	1.0667	1.4373	0.2317	1.6690
VOC	Ppm	0.0798	0.0378	1.3941	0.2472	0.0235	0.2707
PM_1	µg/m³	17.7784	12.8301	1.3800	52.2089	4.4127	56.6217
WS	m/s	0.5723	0.1501	0.6371	0.7266	0.2948	1.0213
Air Temp	°C	27.4927	1.2482	0.0282	5.4920	24.8922	30.3843
Solar Rad.	W/m²	106.8467	32.0178	0.6098	118.1471	63.9829	182.1300
Rain	mm/h	10.3899	12.7273	2.1794	75.0128	0.0000	75.0128

WS – wind speed, Solar Rad. – solar radiation

Table Error! No text of specified style in document.**.2: Descriptive statistics of hourly air pollutants and meteorological parameters obtained from STATION B**

Parameter	Unit	Mean	St. Dev.	Skewness	Range	Min.	Max.
CO	Ppm	0.6896	0.4443	2.4841	4.4714	0.0260	4.4974
VOC	Ppm	0.8942	0.2790	1.2346	3.3315	0.3985	3.7300
PM_1	µg/m³	13.5465	14.7423	2.2621	95.8276	0.3800	96.2076
WS	m/s	1.2328	0.6973	0.7026	4.0400	0.1400	4.1800
Air Temp	°C	27.0674	2.8804	0.7132	18.3000	19.6000	37.9000
Solar Rad.	W/m²	105.5213	161.5718	1.6381	781.7000	0.1000	781.6000
Rain	mm/h	9.6398	85.3950	14.7307	2400.0000	0.0000	2400.0000

WS – wind speed, Solar Rad. – solar radiation

Table Error! No text of specified style in document.**.3: Descriptive statistics of hourly air pollutants and meteorological parameters obtained from STATION C**

Parameter	Unit	Mean	St. Dev.	Skewness	Range	Min.	Max.
CO	Ppm	0.6255	0.4827	3.0082	6.1479	0.0020	6.1499
VOC	Ppm	0.1097	0.0972	3.6619	1.5871	0.0000	1.5871
PM_1	µg/m³	15.4027	15.1455	1.8438	90.4205	0.3300	90.7505
WS	m/s	0.9488	0.4769	0.9610	5.0400	0.1300	5.1700
Air Temp	°C	27.1175	3.0435	0.5746	18.7000	19.0000	37.7000
Solar Rad.	W/m²	98.0040	152.8278	1.6616	736.5000	-0.6000	735.9000
Rain	mm/h	10.2209	95.4209	16.3886	3006.0000	0.0000	3006.0000

WS – wind speed, Solar Rad. – solar radiation.

4.2 Correlation Analysis Results of relationship between Air Pollution and Meteorological Parameters

MS Excel 2019 version was used to compute the correlation matrix via the data analysis tool (Tables 4.4 – 4.6). The purpose of this computation was to find the strength of relationship between the different pollutants as well as pollutants versus meteorological data to generate mathematical model for predicting pollutants concentration.

Table 4.4 shows the correlation results of the relationship between air pollutant variables and meteorological parameters in station A, From the results it was revealed that CO has weak and direct (positive) relationship with air temperature (0.39062) and Solar radiation (0.3606), CO also has weak and inverse (negative) relationship with wind direction (-0.4290) and rain (-0.2849). The results showed that VOC has weak and direct (positive) relationship with air temperature (0.2377), solar radiation (0.2459) and rain (0.1224), and weak and inverse relationship with wind direction (-0.3453). Finally, the results also revealed that PM has strong and direct (positive0 relationship with air temperature (0.5787) and solar radiation (0.70440 but inverse (negative) and weak relationship with wind direction (-0.0650) and rain (-0.4161).

These results imply that increase in air temperature and solar radiation leads to slight increase in dispersal of CO and VOC pollutant, and substantial increase in dispersal of PM_1, whereas increases in wind direction and rain slightly reduces the dispersal of CO and PM_1 but slightly increases the dispersal of VOC.

Table Error! No text of specified style in document.**.4: Correlation matrix for STATION A using the daily data**

	CO (ppm)	**VOC (ppm)**	**PM_1 (μg/m^3)**	**WS (m/s)**	**AIR TEMP (°C)**	**Solar Rad. (W/m^2)**	**RAIN (mm/hr)**
CO (ppm)	1.0000						
VOC (ppm)	0.2337	1.0000					
PM_1 (μg/m^3)	**0.7194**	0.0653	1.0000				
WS (m/s)	-0.429	-0.366	-0.0650	1.0000			
AIR TEMP (°C)	0.3922	0.2377	**0.5787**	-0.2342	1.0000		
Solar Rad. (W/m^2)	0.3606	0.2459	**0.7044**	0.0491	**0.6621**	1.0000	
RAIN (mm/hr)	-0.284	0.1224	-0.4161	-0.1261	**-0.5796**	-0.3885	1.0000

Table 4.5 shows the correlation results of the relationship between air pollutant variables and meteorological parameters in station B, From the results it was revealed that CO has strong and direct (positive) relationship with air temperature (0.5091) and weak direct relationship with Solar radiation (0.3945), CO also has weak and inverse (negative) relationship with wind direction (-0.4640) and rain (-0.3000). The results showed that VOC has weak and inverse (negative) relationship with wind direction (-0.1150) air temperature (-0.2401), solar radiation (-0.1741) and weak and direct relationship with rain (0.4475). Finally, the results also revealed that PM has strong and direct (positive0 relationship with air temperature (0.5191) and solar radiation (0.6527), weak and direct relationship with wind direction (0.0260) but inverse (negative) and weak relationship with rain (-0.3939).

These results imply that increase in air temperature leads to substantial increase in dispersal of CO and PM_1 and slight drop in dispersal of VOC pollutant, increase in solar radiation leads to slight increase in CO dispersal, slight reduction in VOC dispersal and substantial increase in PM_1 dispersal. Increase in wind direction leads to slight reduction in CO, PM and VOC dispersal, while increase in rain results to slight reduction in CO and PM_1 dispersal and slight increase in VOC dispersal, and vice versa

Table Error! No text of specified style in document.**.5: Correlation matrix for STATION B using the daily data**

	CO (ppm)	**VOC (ppm)**	**PM1 (μg/m^3)**	**WS (m/s)**	**AIR TEMP (°C)**	**Solar Rad. (W/m^2)**	**Rain (mm/hr)**
CO (ppm)	1.0000						
VOC (ppm)	0.0439	1.0000					
PM_1 (μg/m^3)	**0.6690**	-0.0964	1.0000				
WS (m/s)	-0.464	-0.1150	0.0260	1.0000			
AIR TEMP (°C)	**0.5091**	-0.2401	**0.5191**	-0.1464	1.0000		
Solar Rad. (W/m^2)	0.3945	-0.1741	**0.6527**	0.0125	**0.6630**	1.0000	

RAIN (mm/hr)	-0.300	0.4475	-0.3939	-0.1812	**-0.5800**	-0.395	1.0000

Table 4.6 shows the correlation results of the relationship between air pollutant variables and meteorological parameters in station C, From the results it was revealed that CO has weak and direct (positive) relationship with air temperature (0.3145) and Solar radiation (0.4108), CO also has weak and inverse (negative) relationship with wind direction (-0.2610) and rain (-0.2232). The results showed that VOC has weak and inverse (negative) relationship with wind direction (-0.3768) and solar radiation (-0.4641) and weak and direct relationship with rain (0.4724) and strong and inverse relationship with air temperature (5561). Finally, the results also revealed that PM has strong and direct (positive0 relationship with air temperature (0.5343) and solar radiation (0.7565), weak and direct relationship with wind direction (0.0509) but inverse (negative) and weak relationship with rain (-0.3939).

These results imply that increase in air temperature leads to substantial increase in dispersal PM_1, substantial drop in dispersal of VOC and slight increase CO pollutant, increase in solar radiation leads to slight increase in CO dispersal, slight reduction in VOC dispersal and substantial increase in PM_1 dispersal. Increase in wind direction leads to slight reduction in CO, PM_1 and slight increase in VOC dispersal, while increase in rain results to slight reduction in CO and PM dispersal and slight increase in VOC dispersal, and vice versa

Table Error! No text of specified style in document.**.6: Correlation matrix for STATION C using the daily data**

	CO (ppm)	**VOC (ppm)**	**PM_1 (g/m^3)**	**WS (m/s)**	**AIR TEMP (°C)**	**Solar Rad. (W/m^2)**	**RAIN (mm/hr)**
CO (ppm)	1.0000						
VOC (ppm)	-0.1477	1.0000					
PM_1 (µg/m^3)	**0.6382**	-0.4955	1.0000				
WS (m/s)	-0.2610	-0.3768	0.0509	1.0000			
AIR TEMP (°C)	0.3145	**-0.5561**	**0.5343**	-0.1323	1.0000		
Solar Rad. (W/m^2)	0.4108	-0.4641	**0.7565**	-0.0715	**0.6858**	1.0000	
RAIN (mm/hr)	-0.2232	0.4724	-0.393	-0.2371	-0.5341	-0.4174	1.0000

4.3 Predictive Modelling Based on Linear Regression using Pollutant Concentration

The variables which are meteorological and air pollutants were combined according to the R^2 values (correlated parameters) to predict the concentration of pollutants. The experimental data in STATION B & C were used for prediction while data from STATION A was used for validation. Linear multiple regression model was developed using the experimental data to predict the concentration of pollutants. The linear regression model was developed via XLSTAT version 2018 an add-in in MS Excel application. This is in line with Doreswamy et al. (2020) who applied Linear regression and other Machine Learning technique to forecast $PM_{2.5.}$ The input parameters were the correlated meteorological data and pollutant concentration. Regression was used to understand the relationship between the dependent variable (pollutant concentration) and independent variables (meteorological parameter & pollutant concentration).

4.3.1 Regression Model for PM_1 (µg/m^3)

Table Error! No text of specified style in document.**.7: Analysis of variance for PM_1**

ANOVA

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	66344.962	66344.962	15188.270	< 0.0001
Error	413	1804.055	4.368		

Corrected Total	414	68149.017

DF=degree of freedom; F=Fischer; MSE= mean square error; RMSE=root mean square error.

Goodness of fit statistics: observations = 415.000, Sum of weights = 415.000, DF = 413.000, $R^2 = 0.974$, Adjusted $R^2 = 0.973$, MSE = 4.368 and RMSE = 2.090.

The correlation coefficient of 0.974 for PM_1 prediction using linear regression is good.

Source	**Value**	**Standard error**	**T**	**Pr > |t|**	**Lower bound (95%)**	**Upper bound (95%)**
Intercept	3.919	0.152	25.743	< 0.0001	3.620	4.218
CO (ppm)	0.631	0.005	123.241	< 0.0001	0.621	0.641

Equation of the model: $$PM_1\ (\mu g/m^3) = 3.91881+0.63099*CO\ (ppm) \quad 4.1$$

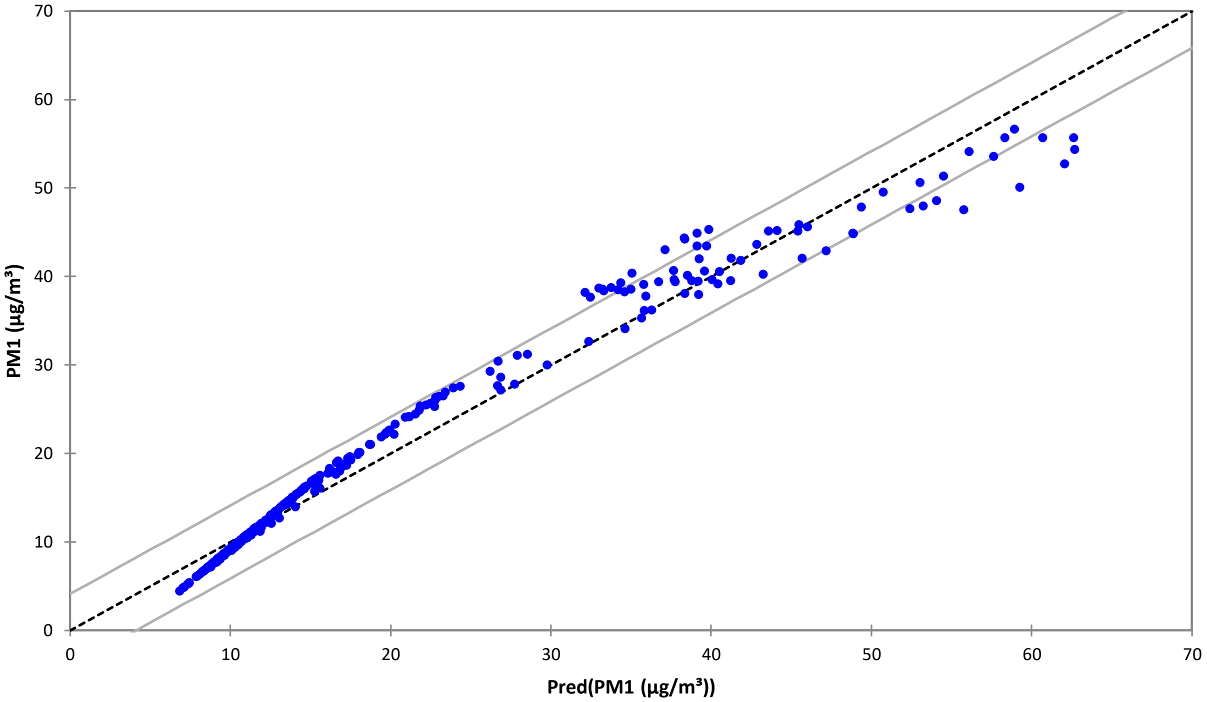

Figure Error! No text of specified style in document..**1: Experimental versus predicted PM_1**

4.3.2 Regression Model for CO_2 (ppm):

Table Error! No text of specified style in document..**2: Analysis of variance for CO_2**

ANOVA

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	2	1850060.566	925030.283	381.626	< 0.0001
Error	412	998654.198	2423.918		
Corrected Total	414	2848714.764			

DF=degree of freedom; F=Fischer; MSE= mean square error; RMSE = root mean square error.

Goodness of fit statistics: observations = 415.000, Sum of weights = 415.000, DF = 412.000, $R^2 = 0.649$, Adjusted $R^2 = 0.648$, MSE = 2423.918, and RMSE = 49.233. Similar to CO prediction, CO_2 correlation coefficient is 0.649 which is not very strong. However, this result agrees with findings of Panda and Nagendra (2017) who used AERMOD for their prediction.

Table Error! No text of specified style in document.**.3: Model parameters for CO_2**

Source	Value	Standard error	T	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	-494.406	49.594	-9.969	< 0.0001	-591.894	-396.918
AIR RH (%)	6.749	0.540	12.509	< 0.0001	5.688	7.809
Solar Rad. (W/m²)	2.901	0.112	25.826	< 0.0001	2.681	3.122

Equation of the model: CO_2 **(ppm) = -494.40565+6.74888*AIR RH (%) +2.90143*Solar Rad. (W/m²) 4.2**

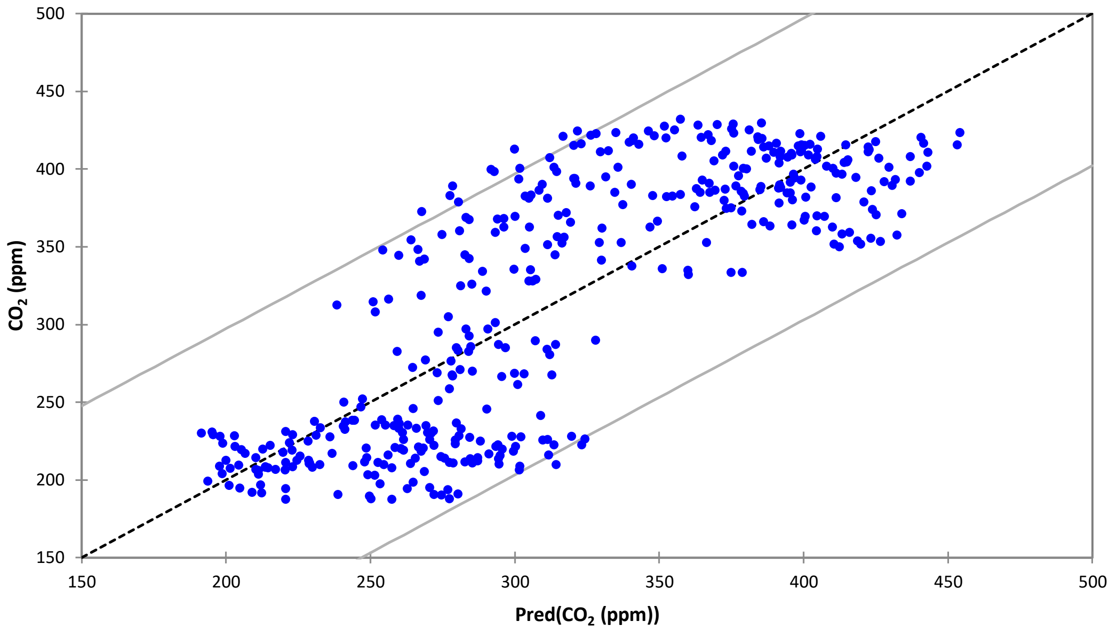

Figure Error! No text of specified style in document.**.2: Experimental versus predicted values of CO_2**

However, the concentration of VOC did not correlate strongly with any parameter it was excluded from the predictive modelling.

REFERENCES

Al-Salem, S. M., & Khan, A. R. (2008). Comparative assessment of ambient air quality in two urban areas adjacent to petroleum downstream/upstream facilities in Kuwait. *Brazilian Journal of Chemical Engineering*, 25, 683-696

Barman, S.C., G.C. Kisku, A.H. Khan, T. Ahmed and P. Shukla et al., (2012). Assessment of ambient air quality of Lucknow City during pre-monsoon, findings of a random survey. Proceedings of the World Environment Day, June 5, 2012, CSIR-*Indian Institute of Toxicology Research*, Mahatma Gandhi Marg, Lucknow, India, pp: 1-26.

Doreswamy, Harishku, K. S., Km, Y., & Gad, I. (2020). Forecasting Air Pollution Particulate Matter (PM2.5) Using Machine Learning Regression Models. In *Procedia Computer Science* (Vol. 171, pp. 2057–2066). Elsevier B.V. https://doi.org/10.1016/j.procs.2020.04.221

Francis Ch, I., Alexander, O., Pascal Chu, N., & Jude Ikech, A. (2017). Ambient Air Quality Assessment of Orlu, Southeastern, Nigeria. *Journal of Applied Sciences*, *17*(9), 441–457. https://doi.org/10.3923/jas.2017.441.457Jerievi et al., 2019).

Nwachukwu A. N., Chukwuocha E. O. and Igbudu O. (2012). A survey on the effects of air pollution on diseases of the people of Rivers State, Nigeria. *African Journal of Environmental Science and Technology Vol. 6(10)*, pp. 371-379, October 2011 Available online at http://www.academicjournals.org/AJEST

Panda, S., & Nagendra, S. M. S. (2017). Assimilative capacity–based emission load management in a critically polluted industrial cluster. *Journal of the Air and Waste Management Association*, *67*(12), 1353–1363. https://doi.org/10.1080/10962247.2017.1372319

Sanchez, N. P., Saffari, A., Barczyk, S., Coleman, B. K., Naufal, Z., Rabideau, C., & Pacsi, A. P. (2019). Results of three years of ambient air monitoring near a petroleum refinery in Richmond, California, USA. *Atmosphere*, *10*(7). https://doi.org/10.3390/atmos10070385

Sanjay, R., (2008). Exposure to bad air raises blood pressure, study shows. *Ohio State University*. http://www.sciencedaily.com/releases/2008/07/080728114 026.htm

Simpson, I.J.; Marrero, J.E.; Batterman, S.; Meinardi, S.; Barletta, B.; Blake, D.R. (2013). Air quality in the Industrial Heartland of Alberta, Canada and potential impacts on human health. *Atmos. Environ*., 81, 702–709.

Tawari, C.C. and Abowei, J.F.N. (2012). Air pollution in the Niger Delta area of Nigeria. *Int. J. Fish*. Aquat. Sci., 1: 94-117.

World Bank (2016). Petroleum Refining. In: World Bank, Ed., *Pollution Prevention and Abatement Handbook*, 1998: *Toward Cleaner Production*, World Bank Group, Washington DC, 377-380.

World Health Organization (2019). WHO Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulphur Dioxide Global Update. *Summary of Risk Assessment*, **23**, 1-20.

Zabbey, N., Sam, K., Newsom, C. A., & Nyiaghan, P. B. (2021). The COVID-19 lockdown: An opportunity for conducting an air quality baseline in Port Harcourt, Nigeria. *Extractive Industries and Society*. https://doi.org/10.1016/j.exis.2020.12.011