The Development of Mathematical Model for Prediction of $PM_{2.5}$ Concentrations in ambient air of Metal Recycling industry in Ogijo, Ogun State, South Western Nigeria

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ABSTRACT

Aims: This study aimed to develop a mathematical model for predicting $PM_{2.5}$ pollutant concentrations in the ambient air of the metal recycling industry.

Study design: This research is a quantitative design andutilized a regression and correlational analysis. Three models were developed for predicting $PM_{2.5}$ concentrations: Linear Regression (LRM), Nonlinear Polynomial Regression (NPRM), and Nonlinear Gamma Regression (NGRM)models. Error evaluation functions were employed to analyze how these models deviated from the experimental data. The applicability of the models was assessed using statistical tools, such as correlation coefficient (r), coefficient of determination (R^2), coefficient of non-determination (K^2), student's t (t-test), equality of variance (F-test), and chi-square ($\chi 2$) tests.

Place and Duration of Study: The study was conducted in the metal recycling industry in Ogijo, Southwestern Nigeria, from November 2021 to October 2022.

Methodology: Daily mean meteorological data including ambient temperature, rainfall, relative humidity (RH), wind speed (WS), wind direction (WD), solar radiation, and ultra-violet radiation were recorded using an automatic weather monitoring system positioned 2.0m above ground level at each sampling location adjacent to the $PM_{2.5}$ sampler. Data were collected at 5-minute intervals and stored in memory, with data retrieval facilitated by the weather-smart program. Data collection commenced during the dry season of 2021 through wet season of 2022.

Results: The analysis of error evaluation functions revealed that the NGRM exhibited the least deviation from the experimental data compared to the LRM and NPRM. Statistical analysis further demonstrated that the NGRM better represented the experimental data compared to the LRM and NPRM, resulting in the rejection of LRM and NPRM in favour of NGRM for predicting $PM_{2.5}$ concentration.

Conclusion: The NGRM proved to be the most suitable model for predicting $PM_{2.5}$ pollutant concentrations in the study area. Temperature and pressure emerged as the most significant predictors of $PM_{2.5}$ levels.

Keywords: Concentration, Mathematical model, Metal Recycling, PM 2.5, Prediction

1. INTRODUCTION

"The investigation of outdoor air pollution has gained significant attention from researchers in recent years due to the severe degradation of air quality in both remote and urban areas" (Aryal et al., 2013; Manisalidis et al., 2020). "Clean air is essential for human health and environmental well-being" (Belis et al., 2014; Manisalidis et al., 2020). "However, major anthropogenic activities such as overpopulation, industrialization, and transportation frequently release toxic substances like particulates, heavy metals, and gases into the atmosphere at concentrations exceeding natural ambient levels, leading to air quality deterioration" (Manisalidis et al., 2020).

"Fine particulate matter ($PM_{2.5}$) is a crucial indicator of air quality. $PM_{2.5}$ emissions originate from various sources, both natural (e.g., windborne dust, sea spray, volcanic activity, biomass burning) and anthropogenic (e.g., fuel combustion, industrial processes, transportation)" (Loomis et al., 2014). "These fine particles can be characterized by their physical attributes and chemical compositions. Physical attributes such as mass concentration (measured in units of mass per unit volume) and size distribution (measured by aerodynamic diameter) influence their transport and deposition. Aerodynamic diameter refers to the equivalent diameter of a spherical particle with the same settling velocity as the collected particles" (Liu et al., 2014; Endale et al., 2024).

"The chemical composition of $PM_{2.5}$ includes inorganic compounds, elemental carbon (black soot), trace elements, and organic compounds, all of which can significantly impact visibility, human health, atmospheric chemistry, climate change, and agriculture" (Basha et al., 2014). "Among these inorganic compounds are toxic metals such as arsenic (As), cadmium (Cd), chromium (Cr), nickel (Ni), vanadium (V), manganese (Mn), lead (Pb), iron (Fe), cobalt (Co), copper (Cu), zinc (Zn), titanium (Ti), and aluminium (Al), which are of serious concern due to their frequent occurrence in residential and occupational areas, with inhalation being a primary route of exposure. The amount of pollutants in a particular location can be influenced by meteorological factors and pollutant sources" (Issah et al., 2024).

"Fine particulate matter ($PM_{2.5}$) has been a focus of attention due to its closer association with adverse health effects and its greater hazard compared to larger particulate matter, owing to its longer residence time in the atmosphere and its ability to act as a carrier of harmful trace metals into the human lungs" (Pope & Dockery, 2006; Feng et al., 2009; Celo&Dabek-Zlotorzynska, 2010; Harrison et al., 2010; AQEG, 2012; Canseco-Lajas et al., 2013; Kim et al., 2015; Basith et al., 2022; Roy et al., 2024).

The Metal Recycling Industrial Estate in Ogijo, Sagamu Local Government Area, with coordinates 3°30'55.8"N and 6°41'57.9"E, is predominantly occupied by metal recycling factories situated in densely populated residential areas. These factories are well connected by accessible roads and are near one another, with similar emission sources. This area hosts one of the largest conglomerates of metal recycling factories in Nigeria, receiving scrap metal-laden trucks from across the country (Olatunji et al., 2018). The recycling process generates billets and iron rods, resulting in high stockpiles of scrap metal and slag waste, and the evolution of toxic fumes. The surrounding land use includes road dust from unpaved roads, construction activities, industrial emissions, commercial activities, refuse burning, toxic fumes from factory chimneys, heavy truck exhaust, and dust pollution from stockpiled metal scraps (Balogun-Adeleye et al., 2022).

Various statistical methods have been developed to determine the relationships between air pollution concentrations and meteorological parameters. These include multiple linear regression analysis (Barrero et al., 2006; Ekum et al., 2015; Bose & Chowdhury, 2023), nonlinear multiple regressions (Cobourn, 2007; Ekum et al., 2023a, 2023b, Metilelu et al., 2023), artificial neural networks (Hooyberghs et al., 2005; Han et al., 2018), and generalized additive models and fuzzy-logic-based models (Cobourn et al., 2000; Barton et al., 2020; Pinilla &Negrín, 2021; Borgue et al., 2022; Almadiet al., 2022; Gerami et al., 2023). These models have been tested for daily or long-term forecasting and exploring the relationship between O_3 and PM. It can be useful to estimate unknown PM air concentration values based on known air concentrations of other pollutants and meteorological variables. General Linear Models (GLM) are often used to estimate PM concentrations based on known values of other air pollutants at the same site (Samir et al., 2016; Arowoloet al., 2017; German et al., 2017; Christopher et al., 2019; Yansui et al., 2020; Ekum&Ogunsanya, 2020; Ekum et al., 2021; Junbeon&Seongju, 2021; Mo et al., 2022; Persis & Amar, 2023; El Mghouchi et al, 2024).

Recent studies have significantly advanced our understanding of the relationship between $PM_{2.5}$ and various environmental and meteorological factors. Studies have expanded on these findings, providing additional insights into the factors influencing $PM_{2.5}$ concentrations and their impacts on human health and the environment. For instance, German et al. (2017) investigated the effects of temperature and humidity on PM concentrations in a subtropical climate during winter, revealing significant correlations that contribute to the understanding of PM dynamics in different environmental settings. The relationship between meteorological conditions and air pollution has also been explored in other regions. Christopher et al. (2019) examined the influence of meteorological parameters on particle pollution in the tropical climate of Port Harcourt, Nigeria, highlighting the complex interactions between local meteorology and $PM_{2.5}$ levels in urban environments.

Furthermore, Zhao et al. (2020) explored the impact of meteorological conditions on $PM_{2.5}$ levels across different seasons in urban China, highlighting significant correlations between air pollution and factors such as temperature, humidity, and wind speed. They found that these meteorological variables influence the concentration and distribution of $PM_{2.5}$ in the atmosphere. Guo et al. (2021) investigated the long-term effects of exposure to $PM_{2.5}$ on respiratory health, emphasizing the critical need for effective air quality management strategies to mitigate health risks associated with particulate matter exposure. Their findings underscored the adverse respiratory health impacts of $PM_{2.5}$ and the importance of reducing exposure levels to protect public health.

Thangavel et al. (2022) discussed the health impact of PM2.5. They mentioned that ambient fine particulate matter ($PM_{2.5}$), which is defined as particles with an aerodynamic diameter of less than 2.5 μm, is widely considered to pose a serious risk to human health based on several epidemiologic and toxicological studies. The respiratory system is primarily responsible for absorbing $PM_{2.5}$, which can then enter the bloodstream by penetrating the lung alveoli. Reactive oxygen or nitrogen species and oxidative stress in the respiratory system cause several illnesses by inducing the production of pulmonary inflammatory mediators. Based on the latest data, cardiopulmonary diseases like heart disease, respiratory infections, chronic lung disease, cancers, preterm births, and other illnesses account for almost 4 million deaths worldwide due to fine particulate matter, or PM2.5.

Amann et al. (2020) discussed the policy effectiveness of $PM_{2.5}$.They mentioned that a significant portion of the current 3–9 million cases of premature deaths per year could be prevented with improved air quality. In addition to providing clean air, these actions of regulating and reducing $PM_{2.5}$would greatly cut greenhouse gas emissions and advance several UN sustainable development objectives. Also, Tariq et al. (2023) discussed the policy effectiveness of PM2.5.In their work, they concluded that low rainfall combined with deforestation and agricultural practices worsens air pollution and desertification, which increased health risks in the study areas.Wei & Li (2023), in their study, opined thatthe global COVID-19 lockdowns were accompanied by wave-like dramatic changes in air quality, and the mortality burden associated with these events is also clearly visible. Remarkably, only about one-third of all nations reach their pre-pandemic levels of pollution. Numerous episodes of air pollution caused by nature are also disclosed, including the burning of biomass.

In the aspect of modelling,Li et al. (2022) developed advanced machine learning models to predict $PM_{2.5}$ concentrations, demonstrating improved accuracy in air quality forecasting. Their study showed that machine learning techniques can effectively capture complex relationships between $PM_{2.5}$ levels and various environmental and meteorological factors, offering valuable tools for air quality management and policy-making (Li et al., 2022). Onanuga et al. (2024) carried out a thorough investigation into seasonal shifts in air pollution in communities close to scrap metal recycling companies in Ogijo, Shagamu South LGA, Ogun State, Nigeria. Carbon monoxide, nitrogen dioxide, sulfur dioxide, $PM_{2.5}$, and PM_{10} concentrations were measured during the dry and wet seasons at 20 key sampling locations and control sites using cutting-edge Gary Wolf Environmental Sensing and Particulate Counting equipment. With some concentrations exceeding Nigerian ambient air quality standards, the results showed significant seasonal fluctuations in pollutant levels, raising serious concerns about environmental health.

So far, recent research has expanded our knowledge of the environmental and meteorological factors influencing $PM_{2.5}$ concentrations. These studies have underscored the need for effective air quality management strategies and provided valuable insights into the impacts of particulate matter on human health and the environment. These reviews synthesize recent studies that have contributed to our understanding of $PM_{2.5}$ and its environmental and health impacts, providing a comprehensive overview of the current state of research in this field.

This work aims to develop a nonlinear regression model to predict $PM_{2.5}$ pollutant concentrations in the ambient air of the metal recycling industry in Ogijo, Ogun State, Southwestern Nigeria. This work serves as a valuable tool for regulatory bodies and researchers to forecast $PM_{2.5}$ concentrations, aiding in policy formulation and decision-making for the benefit of the residentsof Ogun State and Nigeria, considering the adverse effects of particulates on human health and the environment.

2. MATERIAL AND METHODS

2.1 Meteorological Data Collection

The daily mean meteorological data from the parameters such as ambient temperature, rainfall, relative humidity (RH), wind speed (WS), wind direction (WD), solar radiation and ultra-violet radiation, were recorded through an automatic weather monitoring system (professional weather station) mounted at 2.0m above the ground level at each sampling location closely beside the $PM_{2.5}$ sampler. It was programmed to collect data at an interval of 5 minutes and store it in memory. The recorded measurements were downloaded to a computer using the weather-smart.

However, the meteorological data collection started in the dry season, which was observed from January, February, March, April, November and December respectively. The dry season was characterized by the following weather conditions; clear sky, moderate to high solar radiation, moderate to high air temperature, and extremely low precipitation. In addition, the harmattan period was observed from mid-November to mid-February. High dry weather and dusty weather along with low humidity were experienced during this period. This was attributed to the contribution of wind-borne dust due to the North-east trade wind from the Sahara desert. The wet season which was observed from May to October was characterized by moderate rainfall and highly humid conditions.

2.2 Model Development

The Meteorological data generated in this work study from November 2021 to October 2022 were used to develop a mathematical model for the prediction of $PM_{2.5}$ and toxic metals. The data were represented in the form of Equation (1).

$$y = f\ (x_1, x_2, x_3, x_4, x_5, x_6, x_7) \quad (1)$$

where $y$is concentration of $PM_{2.5}$, $x_1$istemperature, $x_2$is humidity, $x_3$ispressure, $x_4$is wind speed, $x_5$is wind direction, x_6 is solar radiation and x_7 is rainfall.

Three (3) different models were obtained using the generated data with the aid of an inbuilt solver tool in R Software version 2024 which is user-friendly. The obtained models were used to predict the experimental data. R was used in this work because it is a statistical programming software which is very user-friendly, flexible and freely available online for download.

2.3 Error Functions Analysis

"To validate how well the predicted data agreed with the experimental data, error evaluation functions analysis models which are mathematical representations of a process, presented in Equations 2-10 were applied to the experimental and predicted data" (Olafadehan, 2021).

Average Relative Error (ARE)

$$(ARE) = \frac{1}{N}\sqrt{\sum_{k=1}^{N}\left(\frac{y_{expt} - y_{pred}}{y_{expt}}\right)^2} \quad (2)$$

where y_{expt} is experimental data, y_{pred} is predicted data, and N is the number of experimental data.

The sum of Error Square (ERRSQ)

$$ERRSQ = \frac{1}{N}\sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right)^2 \quad (3)$$

Marquard Percent Standard Deviation (MPSD)

$$MPSD = \frac{1}{N - N_P}\sqrt{\sum_{k=1}^{N}\left(1 - \frac{y_{pred}}{y_{expt}}\right)^2} \quad (4)$$

where Np = number of parameter(s) to be determined.

Hybrid fractional error function HYBRID)

$$HYBRID = \frac{1}{N - N_P}\sum_{k=1}^{N}\left[\frac{\left(y_{expt} - y_{pred}\right)^2}{y_{expt}}\right] \quad (5)$$

Root Mean Square Error (RMSE)

$$RMSE = \frac{1}{N-2}\sqrt{\sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right)^2} \quad (6)$$

Sum of Absolute Error (EABS)

$$EABS = \sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right) \quad (7)$$

Chi-square test $x^2 = \sum_{k=1}^{N}\left[\frac{\left(y_{expt} - y_{pred}\right)^2}{y_{pred}}\right]$ (8)

Standard error of estimate $(SEE) = \sqrt{\frac{\sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right)^2}{N-2}}$ (9)

Mean relative percentage error $(MRPE) = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{y_{expt} - y_{pred}}{y_{expt}}\right)$ (10)

2.4 Statistical Analysis

Statistical analyses were also investigated on the experimental and predicted data as a supplementary tool for the selection of a suitable model which truly represented the experimental data to a very high level. The statistical tools used in this work are depicted in Equations 11 – 15.

$$r = \frac{\sum_{k=1}^{N}\left(y_{expt} - y_{expt}^{-}\right)\left(y_{pred} - y_{pred}^{-}\right)}{\sqrt{\sum_{k=1}^{N}\left(y_{expt} - y_{pred}^{-}\right)^2 \sum_{k=1}^{N}\left(y_{pred} - y_{pred}^{-}\right)}} \quad (11)$$

where r = Pearson product-moment correlation, $y_{expt}$is the mean value of experimental data, y_{pred} is the mean value of predicted data

$$R^2 = 1 - \frac{\sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right)^2}{\sum_{k=1}^{N}\left(y_{expt} - y_{expt}^{-}\right)^2} \quad (12)$$

where R^2 is the coefficient of determination.

$$K^2 = \frac{\sum_{k=1}^{N}\left(y_{expt} - y_{pred}\right)^2}{\sum_{k=1}^{N}\left(y_{expt} - y_{expt}^{-}\right)^2} \quad (13)$$

where K^2 is the coefficient of non -determination

$$t - test = \frac{\left(y_{expt} - y_{pred}^{-}\right)}{\sqrt{s^2\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}} \quad (14)$$

where s^2 is the standard error, and N_1 and $N_2$are thenumbers of experimental and predicted data respectively.

$$F - test = \frac{\frac{\sum_{k=1}^{N}\left(y_{expt} - y_{expt}^{-}\right)^2}{N-1}}{\frac{\sum_{k=1}^{N}\left(y_{pred} - y_{pred}^{-}\right)^2}{N-1}} \quad (15)$$

3. RESULTS AND DISCUSSION

Three models were developed, namely, Linear regression model (LRM), nonlinear polynomial regression model (NPRM) and nonlinear gamma regression model (NGRM) with the aid of in- built solver tool in R-Software version 2024 as shown in equation (16) – (18). The developed models were used to predict the experimental data.

Table 1. Average monthly values of meteorological parameters generated

Months	Temperature (°C)	Relative Humidity (%)	Pressure (mm/Hg)	Wind speed (Km/h)	Wind direction (°)	Solar radiation (W/m2)	Rainfall (mm)
January	33.8±0.4	68.4±4.8	920.4±0.8	2.54±0.6	96±21	760±64	1.8±0.2
February	32.4±0.6	71.2±2.0	902.6±1.4	2.94±0.7	164±32	740±52	2.0±0.1
March	30.6±0.8	72.4±5.1	918.3±1.2	3.10±0.2	172±18	680±38	2.2±0.4
April	31.2±0.4	73.1±3.6	919.4±0.2	3.42±0.4	184±24	810±42	2.6±0.3
May	28.5±1.2	82.0±2.8	920.5±0.8	2.8±0.2	254±16	98±26	360±32
June	27.4±0.7	83.0±4.4	921.2±0.3	2.7±0.4	262±22	84±32	484±46
July	26.7±0.8	85.0±3.4	923.3±0.6	2.7±0.4	268±28	86±24	540±48
August	28.0±0.5	84.0±6.5	925.6±0.1	2.9±0.3	246±34	140±21	284±26
September	27.8±0.6	78.4±1.8	924.2±0.5	3.2±0.8	210±15	260±38	210±41
October	28.4±0.3	78.8±5.5	924.7±1.5	3.5±0.8	168±26	280±45	148±22
November	29.6±0.4	69.3±2.4	925.2±2.4	2.15±0.3	84±14	810±58	1.4±0.14
December	30.3±1.2	67.5±4.8	925.4±0.3	1.84±0.5	88±17	780±46	0.6±0.1
Dry Season Mean	31.2	7.08	922	2.66	131	764	1.76
Wet Season Mean	27.8	82	923	2.96	207	158	337.7
Annual Mean	29.5	76.3	76.3	2.81	169	461	256.8

Mean ± S.E.M = Mea values ± Standard error of means of six experiments

Table 1 provides an overview of the monthly meteorological data for Ogijo, Southwestern Nigeria, including temperature, relative humidity, pressure, wind speed, wind direction, solar radiation, and rainfall. Temperatures range from a low of 26.7°C in July to a high of 33.8°C in January. The dry season (November to April) has higher temperatures, averaging 31.2°C, compared to the wet season (May to October) which averages 27.8°C. Relative humidity varies between 67.5% in December to 85.0% in July.The wet season exhibits higher relative humidity (average 82%) compared to the dry season (average 71.08%).Pressure readings range from 902.6 mm/Hg in February to 925.6 mm/Hg in August.The wet season shows slightly higher pressure (average 923 mm/Hg) compared to the dry season (average 922 mm/Hg).Wind speeds are generally low, ranging from 1.84 km/h in December to 3.5 km/h in October.There is a slight increase in wind speed during the wet season (average 2.96 km/h) compared to the dry season (average 2.66 km/h).

Wind direction shows significant variability, with angles ranging from 84° in November to 268° in July.The mean wind direction is higher in the wet season (207°) compared to the dry season (131°).Solar radiation is highest in April at 810 W/m^2 and lowest in June at 84 W/m^2.The dry season experiences much higher solar radiation (average 764 W/m^2) compared to the wet season (average 158 W/m^2). Rainfall ranges from a low of 0.6 mm in December to a high of 540 mm in July.The wet season sees substantially more rainfall (average 337.7 mm) than the dry season (average 1.76 mm).Seasonal Averages, for the dry season mean, temperature: is 31.2°C, relative humidity is 71.08%, pressure is 922 mm/Hg, wind speed is 2.66 km/h, wind direction is 131°, solar radiation is 764 W/m^2,rainfall is 1.76 mm. For the wet season mean, temperature is 27.8°C, relative humidity is 82%, pressure is 923 mm/Hg, wind speed is 2.96 km/h, wind direction is 207°, solar radiation is 158 W/m^2, and rainfall is 337.7 mm. The annual means, temperature is 29.5°C, relative humidity is 76.3%, pressure is 923 mm/Hg, wind speed is 2.81 km/h, wind direction is 169°, solar radiation is 461 W/m^2, and rainfall is 256.8 mm.

The data indicates significant seasonal variations in meteorological parameters, with higher temperatures, lower humidity, and greater solar radiation during the dry season, contrasted by higher humidity, increased rainfall, and slightly higher wind speeds during the wet season. These variations are critical for environmental and health assessments, particularly in predicting pollutant concentrations like PM2.5. The monthly average

Table 2. Average monthly $PM_{2.5}$values generated in the year

Months	**$PM_{2.5}$**
January	389.60±0.00
February	320.44±0.01
March	299.25±0.8
April	281.65±0.01
May	78.22±0.01
June	57.44±0.14
July	46.33±0.01
August	65.61±0.25
September	92.45±0.14
October	109.84±0.01
November	310.39±0.01
December	329.54±0.01
Annual Mean	198.40±132.26

Mean ± S.E.M = Mean values ± Standard error of means of six experiments

Table 2 presents average monthly $PM_{2.5}$ values over a year, it is evident that there are significant variations in $PM_{2.5}$ concentrations across different months.High $PM_{2.5}$concentrations were recorded in the dry season, January is 389.60 μg/m³, February is 320.44 μg/m³, March is 299.25 μg/m³, April is 281.65 μg/m³, November is 310.39 μg/m³ and December is 329.54 μg/m³. These months correspond to the dry season, characterized by minimal rainfall and higher temperatures. The lack of precipitation likely leads to less removal of particulate matter from the air, resulting in higher $PM_{2.5}$ levels.Lower $PM_{2.5}$concentrations were recorded in wet season, May is 78.22 μg/m³, June is 57.44 μg/m³, July is 46.33 μg/m³, August is 65.61 μg/m³, September is 92.45 μg/m³ and October is 109.84 μg/m³. The wet season, with increased rainfall and relative humidity, shows significantly lower $PM_{2.5}$ levels. Rain helps wash away particulate matter from the atmosphere, leading to reduced concentrations.The annual mean $PM_{2.5}$ concentration is 198.40 μg/m³ with a standard deviation of 132.26 μg/m³, indicating high variability in $PM_{2.5}$ levels throughout the year.

Elevated $PM_{2.5}$ levels in the dry season may pose serious health risks, including respiratory and cardiovascular problems, due to prolonged exposure to high concentrations of fine particulate matter.Lower $PM_{2.5}$ levels during the wet season suggest improved air quality, which may reduce the risk of health issues related to air pollution.The observed seasonal trend in $PM_{2.5}$ concentrations correlates with meteorological parameters such as rainfall, temperature, and relative humidity. Understanding these relationships can aid in developing strategies to mitigate air pollution.The sharp decline in $PM_{2.5}$ levels from April to May, and the subsequent low values during the wet season, highlight the role of increased rainfall in reducing air pollution.The high $PM_{2.5}$ levels in the dry season might be attributed to increased industrial activities, vehicular emissions, and dust from dry conditions.Implementing stricter pollution control measures during the dry season could help manage and reduce $PM_{2.5}$ concentrations, improving overall air quality.

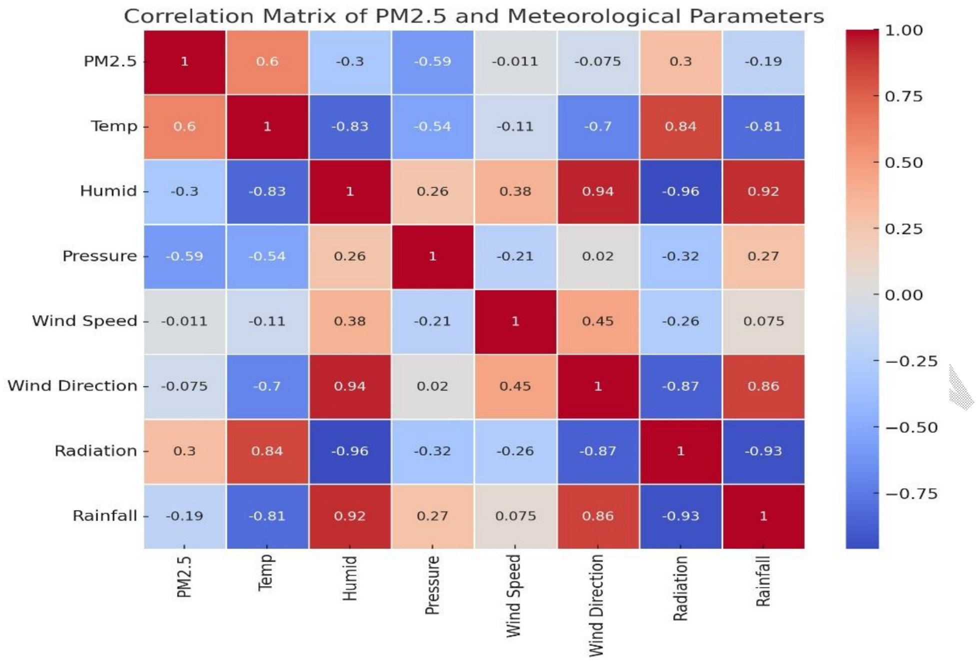

Fig. 1.Correlation between PM2.5 and the Meteorological Parameters

The correlation matrix in Figure 1 provides insights into the relationships between $PM_{2.5}$ concentrations and various meteorological parameters. There is a moderate positive correlation between $PM_{2.5}$ levels and temperature. Higher temperatures are associated with higher $PM_{2.5}$ concentrations.There is a weak negative correlation between $PM_{2.5}$ levels and humidity. Higher humidity tends to be associated with lower $PM_{2.5}$ concentrations.There is a moderate negative correlation between $PM_{2.5}$ levels and atmospheric pressure. Higher pressure is associated with lower $PM_{2.5}$ concentrations.There is an extremely weak negative correlation between $PM_{2.5}$ levels and wind speed, suggesting wind speed has little to no direct impact on $PM_{2.5}$ concentrations.There is a very weak negative correlation between $PM_{2.5}$ levels and wind direction, indicating minimal impact of wind direction on $PM_{2.5}$ concentrations.There is a weak positive correlation between $PM_{2.5}$ levels and solar radiation. Higher solar radiation is slightly associated with higher $PM_{2.5}$ concentrations.There is a weak negative correlation between $PM_{2.5}$ levels and rainfall. Higher rainfall tends to be associated with lower $PM_{2.5}$ concentrations, likely due to the washout effect of rain removing particulate matter from the atmosphere.These correlations help us understand how different meteorological factors impact $PM_{2.5}$ concentrations, which is crucial for developing strategies to manage and mitigate air pollution. The moderate to strong correlations between $PM_{2.5}$ and factors like temperature, pressure, and solar radiation indicate that these variables are significant predictors of $PM_{2.5}$ levels.

Tables 3, 4 and 5 show the experimental and predicted data for each of the developed models.

Table 3. LRM parameter estimation of $PM_{2.5}$

	Estimate	Std. Error	t-stat	P-value
Intercept	-1172.02	7260.294	-0.161	0.8796
Temp (x1)	69.5499	31.9917	2.174	0.0954
Humid (x2)	-38.2725	32.247	-1.187	0.3010

Pressure (x3)	1.8065	7.4553	0.242	0.8205
WindSpeed (x4)	42.0393	112.8568	0.373	0.7284
WindDirection (x5)	2.3677	1.8914	1.252	0.2788
Radiation (x6)	-0.1999	0.4042	-0.495	0.6468
Rainfall (x7)	0.6108	0.6168	0.99	0.3781

Table 3 shows that all the parameters are not significant at the 5% level using the linear regression model (LRM). The developed LRM model is fitted thus

$$y = -1172.018 + 69.549x_1 - 38.273x_2 + 1.807x_3 + 42.039x_4 + 2.368x_5 - 0.2x_6 + 0.611x_7 \quad (16)$$

Table 4. NPRM parameter estimation of $PM_{2.5}$

	Estimate	Std. Error	t-stat	P-value
Intercept	5.75E+05	8.06E+05	0.714	0.605
x1	-1.24E+04	1.15E+04	-1.078	0.476
x2	-4.40E+02	4.55E+03	-0.097	0.939
x3	-6.16E+02	8.57E+02	-0.719	0.603
x4	-5.28E+04	7.84E+04	-0.674	0.622
x1:x2	2.04E-01	4.37E+00	0.047	0.97
x1:x3	1.32E+01	1.23E+01	1.079	0.476
x1:x4	6.90E+01	1.68E+02	0.411	0.752
x2:x3	4.43E-01	4.85E+00	0.091	0.942
x2:x4	1.14E+01	4.72E+01	0.241	0.849
x3:x4	5.40E+01	7.70E+01	0.702	0.610

Table 4 shows that all the parameters are not significant at the 5% level using a nonlinear polynomial regression model (NPRM). The developed NPRM model is fitted thus

$$y = 575300 - 12350x_1 - 440.2x_2 - 616x_3 - 52840x_4 + 0.204x_1x_2 + 13.22x_1x_3 + 68.96x_1x_4 + 0.443x_2x_3 + 11.4x_2x_4 + 54.04x_3x_4 \quad (17)$$

Table 5. NGRM parameter estimation of $PM_{2.5}$

	Estimate	Std.Error	t-stat	P-value
Intercept	-5.83E+01	3.01E+00	-19.412	0.0328
x1	1.01E+00	3.86E-02	26.178	0.0243
x2	1.42E-01	1.62E-02	8.767	0.0723
x3	6.15E-02	3.15E-03	19.495	0.0326
x4	5.99E+00	3.18E-01	18.864	0.0337
x1:x2	1.55E-04	1.11E-05	14.007	0.0454
x1:x3	-1.07E-03	4.02E-05	-26.47	0.0240
x1:x4	-1.50E-02	7.23E-04	-20.735	0.0307
x2:x3	-1.47E-04	1.69E-05	-8.678	0.0730
x2:x4	-3.80E-03	2.14E-04	-17.709	0.0359
x3:x4	-5.70E-03	3.06E-04	-18.599	0.0342

Table 5 shows that all the parameters and their two-way interactions are significant at a 5% level, except for x2 and x2x3 using the nonlinear Gamma regression model (NGRM).

The developed NGRM model is fitted thus

$$y = 1/(-58.3 + 1.011x_1 + 0.142x_2 + 0.062x_3 + 6x_4 + 0.0002x_1x_2 - 0.0011x_1x_3 - 0.015x_1x_4 - 0.00015x_2x_3 - 0.0038x_2x_4 - 0.0057x_3x_4) \quad (18)$$

Table 6. Experimental and predicted values of $PM_{2.5}$

Months	yexpt	LRM ypred	NPRM pred	NGRM ypred
January	389.60	406.89	388.06	389.54
February	320.44	352.14	319.20	320.40
March	299.25	247.17	313.84	299.77
April	281.65	280.22	271.22	281.28
May	78.22	254.11	335.21	311.27
June	57.44	233.87	286.52	328.02
July	46.33	160.44	107.10	79.24
August	65.61	82.45	46.41	57.05
September	92.45	138.52	30.93	45.79
October	109.84	37.15	77.27	66.02
November	310.39	33.96	99.32	92.69
December	329.54	153.85	105.66	109.69

Table 6 displays the experimental values and the predicted values using the three models. The result shows that NGRM predicted values for January to April coincide with that of the experimental values.

Error evaluation functions analysis is a mathematical tool useful for extracting worthwhile information from the experimental values because there is the possibility of experimental values deviating from their true values. The several error evaluation functions used to estimate the error deviation when the developed models were applied to fit the experimental data are shown in Table 7. The error evaluation functions analysis was used in the selection of the best model among the developed models, which best represents the experimental data.

Table 7. Error evaluation function values of the $PM_{2.5}$developed models

Error Function Model	LRM ypred	NPRM ypred	NGRM ypred
ARE	0.20686	0.0492	0.0017
ERRSQ	3199.29	348.8617	0.4350
MPSD	0.57576	-0.0061	-0.0002
HYBRID	99.6729	-14.6753	-0.0183
RMSE	19.5937	6.4701	0.2284
EABS	-7.297e-12	-4.46e-10	-2.68e-08
SEE	61.9608	20.4605	0.7225
MRPE	-0.1919	-0.0010	-3.6278e-05

Table 7 shows that the values for the error function models were ARE .2069, .0492 and .0017 for LRM, NPRM and NGRM respectively. A"RE is used to evaluate the goodness of fit of predicted data with the experimental data. It minimizes the fractional error distribution across an inclusive range of data" (Rahman et al, 2008). The lower the value of ARE, the better the prediction. NGRM has the lowest value of ARE, which indicates the best prediction of the experimental data among the developed models. ERRSQ is a tool that is used to identify the spread of data and how well certain data will fit a model in regression analysis. It is one of the error evaluation functions commonly used. The ERRSQ values were 3199.29, 348.86 and .4350 for LRM, NPRM and NGRM respectively. The smaller the ERRSQ value, the better the model predicts the experimental data. This revealed that NGRM was the best fit for predicting experimental data due toits lowest value of ERRSQ.

The MPSD values were .0578, .0552 and .03072 for LRM, NPRM and NGRM, while HYBRID values were 99.673, -14.6753 and -.0183 for LRM, NPRM and NGRM. The lower the MPSD and HYBRID values, the better the goodness fit hence NGRM has the best goodness fit among the developed models. RMSE provides information about the performance of a model. However, the drawback is that a few large errors in the sum are likely to produce a noticeable increase in RMSE. Large values of RMSE indicate large errors which means models with large RMSE must be avoided. In this work, NGRM has the lowest value of RMSE which means NGRM has the lowest error in predicting the experimental data. SEE measures variation between experimental and predicted data. It is important to check the accuracy of prediction. The smaller the SEE values, the better the prediction. The SEE values for the developed models were 61.9608, 20.4605 and .7225 LRM, NPRM and NGRM respectively.

Statistical evaluation tools were also used to analyse the experimental and predicted with a view of investigating the applicability of the developed models to adopt the best among the developed models which truly represents the experimental data. The statistical evaluation tools employed in this study are presented in Table 8.

Table 8. Statistical evaluation values of the $PM_{2.5}$developed models

Criteria	LRM ypred	NPRM ypred	NGRM ypred
R	0.8947	0.9890	0.9999867
R2	0.8005	0.9782	0.9999867
K2	0.1995	0.0217	2.7132e-05
t-test	-2.858e-14	-1.6944e	-1.014e-10
F-test	1.24923	4.497	1.0015
$\chi2$	12.3734	29.8611	0.0365
AIC	148.9027	128.3106	55.8950

Table 8 shows the error function criteria for the models. In Table 8, the r value for LRM, NPRM and NERM were .8947,.9890 and .9990 respectively. The r values indicate the degree of correlation of the linear relationship between the experimental and predicted data. The values range between -1 and +1 which shows the degree of linearity. The value r close to -1 and +1 indicates a strong negative and positive relationship between the experimental and predicted data. In this study, the NGRM has the highest value of r inthe study location which revealed NGRM to be the best model amongst the developed models. Therefore NGRM was accepted while LRM and NPRM were rejected.

The R^2 is the proportion of the variation in the predicted data that is predictable from the experimental data. R^2 provided more information than ERRSQ, MPSD, RMSE and SEE in regression analysis evaluation as the former can be expressed as a percentage while the latter measures have arbitrary ranges. A high R^2 value indicates that the model is a good fit for the data. The R^2 values in this study were 8005,.9782 and .9990 for LRM, NPRM and NGRM. NGRM had the highest values of R^2 in the study area. This indicated that NGRM is the best model amongst the developed models as it predicted 90.72 per cent of the experimental data. Therefore the NGRM can be selected as the best model for the prediction of PM pollutant concentrations in the Metal recycling industry in the Ogijo area of Sagamu local government in Ogun state.

The K^2 explains the amount of unexplained and unaccounted for, between experimental and predicted data. The smaller the K^2 value, the better the model. The K^2 values in this work were .1995, .0217 and.00002713. NGRM had the least K^2 values from the study area amongst the other developed models which revealed that less than 10 per cent of experimental data were not accounted for by the NGRM. This implied that NGRM best represented the experimental data when compared with LRM and NPRM. The t-test is a type of inferential statistics for determining if there is a significant difference between the means of two groups. It is used when the sample size is less than 30.

The t-test values in this work were 2.858e-14, -1.6944e-12 and -1.014e-10 for LRM, NPRM and NGRM. The t-test values were obtained at 2 tails, 1 pair and at P = .05. The critical value was 2.07. All the t-test values were less than the critical values which implied the null hypothesis cannot be rejected that is the mean values of the experimental and predicted data are statistically significantly equal. However, the model with the least t-test value normally gives the best representation of the experimental data. Based on this, NGRM was chosen while LRM and NPRM were ignored.

The F-test is a statistical tool in which the test statistic has an F-distribution under the null hypothesis. It is widely and often used when comparing and analysing statistical models which have been fitted to a data set to select the model that best fits the experimental data. The F–test values obtained were 1.2492, 4.497 and 1.0015 for LRM, NPRM and NGRM. The critical value was 2.28. This showed that the F-test values were less than the critical value which indicated that the null hypothesis which was that the means of experimental and predicted data were statistically significant and equal at a 5 per cent significant level cannot be rejected. Since the entire developed model passed the F–test, the model with the lowest value of the F-test will give the representation of the experimental data. Therefore NGRM was adopted as the best model while LRM and NPRM were jettisoned.

The χ^2 test is a test which measures how a developed model compares to experimental data. It compares the size of discrepancies between the experimental and predicted data. The 2-test shows whether the experimental and predicted data are related or not and can also be used to test the goodness fit between experimental and predicted data. The χ^2-test values in this study were 12.373, 29.8611 and 0.0365 for LRM, NPRM and NGRM. This implies that the null hypothesis which was that no significant difference between the experimental and predicted data cannot be ignored. This means there is no significant difference between the experimental and predicted data from the developed models. Since the developed models scaled through the χ^2-test, the model with the lowest value of the χ^2-test, which is NGRM, was chosen as the best model that represented the experimental data at P =.05.

Based on the error evaluation functions analysis carried out in this work to evaluate the error deviation of the developed models, it is clear that NGRM has the least deviation from the experimental data when compared with LRM and NPRM. This was also the case in the work of Bing et al. (2021) which used error functions for the section of the best model among the developed models. Therefore LRM and NPRM were jettisoned NGRM was adopted as the mathematical model for the prediction of PM pollutant concentrations in the study area. Moreover, it is obvious based on the statistical evaluation tools used to investigate the applicability of the developed models, that NGRM truly represented the experimental data than LRM and NPRM, which further justified the adoption of the NGRM model for the prediction of PM concentrations in Ogiju.in Ogun State.

Licheng et al. (2021) used nonlinear regression to predict the exposure of air pollutants. The nonlinear model predicted the air pollutants exposure up to 90 per cent. His work also stated that nonlinear models are more accurate than linear models. This is in support of this work in adopting a nonlinear regression model. However,Licheng et al., (2021) did not indicate which non-linear model is better between NPRM and NERM which this work has established. This work has shown that NGRM is better predicted more accurately than other models. However, Salami (2022) selected a non-exponential regression model NERM as the best model but in this study, NGRM is the best model which is a substitute for NERM. This is because the data at hand is more of a gamma distribution than an exponential distribution.

4. CONCLUSION

In conclusion, findings highlight the seasonal variability in $PM_{2.5}$ concentrations, with higher levels during the dry season and lower levels during the wet season, underlining the influence of meteorological conditions on air quality. These insights are crucial for devising effective air pollution management strategies to safeguard public health. The findings from the correlation suggest that temperature, humidity, pressure, and solar radiation are significant predictors of $PM_{2.5}$ concentrations, with temperature and solar radiation having positive influences, while humidity, pressure, and rainfall help in reducing $PM_{2.5}$ levels. These insights can inform strategies for managing air quality in the metal recycling industry, particularly in mitigating $PM_{2.5}$ pollution during hotter, drier periods.

The mathematical model for the prediction of $PM_{2.5}$ pollutants concentrations in Ogijo town in Ogun state has been developed using the in-built solver tool in R Software version 2024. LRM, NPRM and NGRM were developed and subjected to error evaluation functions analysis to determine the deviation of the developed models from experimental data. The applicability of the developed models was also investigated using statistical tools. The NGRM showed the least deviation from the experimental data when compared with LRM and NPRM. Furthermore, NGRM has the highest accuracy in the prediction of the experimental data in terms of statistical analysis when compared with LRM and NPRM hence LRM and NPRM were jettisoned and NGRM was adopted for the navigation of the experimental data generated for $PM_{2.5}$ pollutants concentrations in Ogijo town. It was concluded that the NGRM can be used to predict the PM pollutant concentrations in Ogijo, Ogun state. Southwestern Nigeria.

Based on the results obtained and conclusions drawn from the study, here are the policy implications. The nonlinear gamma regression model (NGRM) was found to be the best model for predicting $PM_{2.5}$ concentrations in Ogijo, Ogun State. This implies that policymakers and environmental agencies should consider adopting NGRM for predicting and monitoring PM2.5 levels in the area due to its superior accuracy and statistical robustness compared to linear and polynomial regression models. The NGRM demonstrated high accuracy and reliability in predicting $PM_{2.5}$ concentrations, with the highest values for R^2 and the lowest error metrics (RMSE, SEE) compared to LRM and NPRM. This suggests that NGRM can provide more precise estimates of PM2.5 levels, crucial for effective air quality management and health risk assessments.

The findings underscore the importance of continued environmental monitoring efforts, especially in areas near metal recycling industries like Ogijo. Regular monitoring using accurate predictive models like NGRM can provide early warning of potential health risks associated with PM2.5 pollution, enabling timely interventions and policy adjustments. Policymakers should encourage the adoption of NGRM for air quality management purposes, providing support for its integration into environmental monitoring frameworks. There is a need to enhance the existing air quality monitoring infrastructure in Ogijo and similar industrial areas, ensuring comprehensive coverage of PM2.5 pollution levels. Policies should include provisions for public health awareness programs to inform residents about the health risks associated with PM2.5 pollution and the measures they can take to minimize exposure. Strengthen regulations governing metal recycling industries to reduce emissions of $PM_{2.5}$ and other pollutants, aiming for compliance with international air quality standards.

Further research and development encourage further research into refining the NGRM and other predictive models to improve their accuracy and applicability in different environmental conditions and geographic areas. Support research into the impacts of $PM_{2.5}$ pollution on vulnerable populations, including children, the elderly, and individuals with pre-existing health conditions. International collaboration to foster collaboration with international environmental agencies and research institutions to leverage global expertise and best practices in air quality management and predictive modelling.

Thus, the adoption of the NGRM for predicting $PM_{2.5}$ concentrations in Ogijo, Ogun State, can significantly enhance environmental and public health outcomes. These policy implications aim to guide decision-makers in developing effective strategies to mitigate the adverse effects of $PM_{2.5}$ pollution and improve air quality in the region.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during the writing or editing of manuscripts.

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