



REMEDIATION OF CRUDE OIL-CONTAMINATED SOIL USING VERMICOMPOST IN THE NIGER DELTA AREA OF NIGERIA

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ARTICLE INFORMATION

Submitted 20 April, 2023

Revised 13 Nov, 2023

Accepted 20 Nov, 2023

Keywords:

ANFIS

ANN

Crude-oil

Contaminated soil

Remediation

Vermicompost

ABSTRACT

Vermicompost is the product of the decomposition process using various species of worms, to create a mixture of decomposing vegetable or food waste, bedding materials, and vermicast. This process is called vermicomposting, while the rearing of worms for this purpose is called vermiculture. Adsorption of toxic metals has been achieved using Vermicompost, but there is dearth of knowledge in adsorption of crude oil using Vermicompost. This study brings to knowledge the effectiveness of earthworm waste (vermicompost) use for the remediation of crude oil contaminated soils. The remediation methods adopted were batch and column processes conditions. Characterization of the vermicompost and crude oil contaminated soil were performed before and after the soil washing using Fourier transform infrared (FTIR), scanning electron microscopy (SEM), X-ray fluorescence (XRF), X-ray diffraction (XRD) and Atomic adsorption spectrometry (AAS). The optimization of washing parameters, using response surface methodology (RSM) based on Box-Behnken Design was performed on the data from laboratory experiments. Machine learning models [Artificial neural network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS). ANN and ANFIS were evaluated on the observed and predicted percentage removal of crude-oil using the coefficient of determination (R^2) and mean square error (MSE)]. Removal efficiency ranged from 29% to 98.9% for batch process remediation and 56% to 92% for column process remediation. Optimum values of the experimental factors were absorbent dosage of 34.53 g, adsorbate concentration of 69.11 (g/ml), contact time of 25.96 (min), and pH value of 7.71, for batch and column processes. Removal efficiency obtained from the multilevel general factorial design experiment ranged from 56% to 92% for column process remediation and 56% to 92% for column process remediation with the same optimum values of factors. Coefficient of determination (R^2) for ANN was (0.9974) and (0.9852) for batch and column process, respectively. This result show strong correlation between the observed and predicted values for batch and column process, respectively, the coefficient of determination (R^2) for RSM was (0.9712) and (0.9614), which also demonstrates agreement between observed and predicted values. For the batch and column processes, the ANFIS coefficient of determination was (0.7115) and (0.9978), respectively. Machine learning models appear to be capable of predicting the removal of crude oil from polluted soil using vermicompost.

1.0 Introduction

The amount of contaminated soil in the world is rising steadily and is getting harder to control (Ahmad et al., 2020; Akinwumi et al., 2014). One major contributor to soil contamination is the petroleum industry. This contamination occurs through effluent discharges and accidental oil spillages (Ordinoha and Brisibe, 2013). Hutchful (1985) claimed that the Funiwa-5 well blowout by Texaco in 1980 caused the spilling of around 400,000 barrels of crude oil into the Atlantic Ocean in the Niger Delta Area of Nigeria. Damaged oil pipeline carrying crude oil from the Idaho oil field to the Qua Iboe terminal bursted on January 12, 1998, releasing almost the same amount of crude oil into the ocean. This incident happened at Iwochang community Akwa-Ibom State, Nigeria. If not cleaned up the right away, spills of petroleum products, particularly crude oil or its derivatives (a liquid hydrocarbon), whether intentional or unintentional, have a harmful impact on the environment. Environmentally harmful effects of oil spills have been well documented in the literature (Adedokun and Ataga, 2006; Daka and Ekweozor, 2004; Ite et al., 2013; Jack et al., 2005). The Niger Delta region of Nigeria has an urgent need for the creation and application of a more comprehensive, effective, and environmentally friendly remediation technique. To arrest the threat and prevent the extinction of this natural gift called soil, effective and environmentally friendly remediation techniques must be adopted (Ite et al., 2013; Jack et al., 2005). In order to provide the basic necessity (food, shelter, water, and energy), soil remediation and restoration have also become critical tasks globally (Gighi et al., 2012). Phytoremediation techniques have been tried in the past, but the remediation of crude oil contaminated soil using this technique is limited to the depth of the plant roots.

Vermicompost is a term for an organic fertilizer created by earthworms feeding on waste products, primarily those with a biological origin (Yatoo et al., 2021). It is thought to be one of the best nutrient sources for plants and aids in improving the physiochemical characteristics of crops (Lim et al., 2015). Yatoo et al., (2021) show that vermicompost improves soil health, fertility, mineral content, aeration, and tilt, which decreases the soil's propensity to compress due to the fact that it does not contain hazardous enzymes and is therefore an environmentally friendly organic product (Adhikary, 2012). As a result of the soil's rich organic matter content, which encourages nutrient adsorption and root growth, vermicomposting aids in increasing the soil's ability to retain water (Mohammadi-Moghadam et al., 2022). By encouraging native microorganisms, adding more nutrients and oxygen to the soil, or introducing microbial consortiums that are abundant in the soil, crude oil-contaminated soils can be improved (García-Díaz et al., 2013; Rein et al., 2016). Some microorganisms can minimize or remove petroleum compounds by using oil compounds as a source of carbon and energy (Amin et al., 2017; Sonwani et al., 2018). The use of chemicals and plants (Phytoremediation) for soil cleanup are either ineffective or prohibitively expensive. The chemical method can be very expensive while phytoremediation is limited to the root depth of the plant. One of the most affordable approaches for soil remediation is composting, which can boost soil organic matter content and soil fertility. (Chen et al., 2015). One of the most affordable solutions for soil bioremediation is composting, the main procedure for stabilizing municipal and agricultural solid waste through the decomposition of biodegradable components by microbial communities or earth worms (Chen et al., 2015; Dores-Silva et al., 2019; Kästner and Miltner, 2016). Vermicompost affects the physical, chemical, and biological characteristics of soil since it contains a variety of microorganisms, including compost (fertilizer) and vermi (earthworms) (Thapa et al., 2012; Wang et al., 2012). For the first time, Davis gave a concise description of the use of biological procedures, which had been known for 80 years (de Souza Pohlen et al., 2019; Medina et al., 2018). The worms are extremely tolerant of various contaminants, according to a case study of Polycyclic Aromatic Hydrocarbons removed from soil employing vermiremediation (Rajiv et al., 2010). Rajiv et al. (2010) discovered that worms like *Eisenia fetida* may take PAH chemicals and remove them from contaminated soils by absorbing them into their bodies. *Sedum alfredii* and pig manure vermicompost (PMVC) was employed in a

study to remove simultaneous contamination of PAHs and cadmium compounds, and the researchers discovered that when the two were used together, the majority of PAHs were eliminated (Wang et al., 2012). Wang et al. (2012) also mentioned that combining pig manure vermicompost with other biological elimination techniques will help to remove contaminants.

Artificial neural network (ANN) is a modeling technique based on the brain's neural structure and it is generally used to model and optimize complex processes (Agatonovic-Kustrin and Beresford, 2000; Rivera et al., 2010). Therefore, ANN analyzes complex variables to form a deterministic equation (Kose, 2008). Artificial neural fuzzy inference system (ANFIS) combines ANN and fuzzy logic techniques to predict the behavior of variables and improve error tolerance, adaptability, and speed of the process (Nwosu-Obieogu et al., 2022; Okolo et al., 2020; Roy et al., 2019). Notwithstanding, the main drawback of the ANN and ANFIS approaches has been the difficulty in determining the model's optimal size and its persistence in local minima (Onu et al., 2021a, Nwosu-Obieogu et al., 2022; Yilmaz and Yuksek, 2009). In another study, Asadu et al. (2022) examined the use of ANN and ANFIS to forecast the removal of crude oil from soil and surface water. Ani and Agu, (2022) reported that ANFIS and ANN have been successfully compared and evaluated as effective modeling techniques for the degradation of crude oil. Souza et al., (2018a) compared ANN and ANFIS in modeling nickel adsorption using agro-waste, and the models predicted the process efficiently. Okolo et al. (2020) used ANN and ANFIS to estimate cadmium (II) biosorption using rice straw, and the models performed remarkably well in predicting removal effectiveness. However, there is a paucity of material on soft computing prediction or a comparison of ANN and ANFIS models for foretelling crude oil removal using vermicompost in the literature. There is also sparse literature on the removal of crude oil contaminants using vermicompost. Hence, this study bridges the existing knowledge gap in the literature by using ANN and ANFIS in predicting crude oil removal using vermicompost.

2.0 Materials and Methods

2.1 Soil sampling and preparation

The soil used for this study was collected from Iwochang community in Ibeno Local Government Area of Akwa-Ibom State, Nigeria (Latitude 4° 33' 54.2"N and Longitude 8° 4' 21.3"E) which has a prior history of crude oil contamination. A sampling area of 200 by 200 m² was randomly selected at surface (0-15cm) and subsurface (15-30cm) depths. The soil samples were placed in paper bags made of aluminum foil, given labels, and transported to a lab for examination. The soil clumps were broken to get homogeneity. The soil was air dried and sieved using <2.0 mm mesh. At the time of sampling, soil pH was monitored, and moisture content in the samples was at the normal threshold for biological elimination procedures (40 to 50% of water holding capacity). According to the American Society for Testing and Materials, an analysis of soil grinding was performed (ASTM-D-2487) (Ryan et al., 2001).

Vermicompost (adsorbent) characterization

The bulk quantity of vermicompost used, was obtained and shipped from agro-chemicals and fertilizer company, London, UK. and it was prepared using laboratory standard following the method adopted by Nwosu-Obieogu et al. (2022). The prepared vermicompost was characterized using FTIR (PerkinElmer Spectrum one v3.02 FTIR spectrometer, India). The surface morphology was determined using scanning electron microscopy SEM (HITACHI S-5500, Japan). Vermicompost in various concentrations (2, 4, and 6%), each of which already has quality indicators had been identified and specified were added to each sample individually.

2.2. Experimental design

In this work, the full factorial design procedure in Design-Expert 13 was used to estimate sample size. Testing was done in triplicate, including sampling, to maximize the tests' precision

and accuracy. Twenty-nine (29) experimental runs were conducted to examine each independent variable at three different levels

2.3. Batch adsorption studies

To test the effects of adsorbent dosage, soil solution ratio, pH, and contact time on the elimination of crude oil from contaminated soil samples, soil washing was done in batches (Nwosu-Obieogu et al., 2022). The contaminated soil sample was thoroughly mixed the prepared Vermicompost before placing it on the mechanical shaker.

125 ml conical flask batch tests were performed over rotary shaker at 200 rpm, following the method adopted by Adedokun and Ataga, 2006 to ensure homogeneous mix. All experiments were carried out for a defined contact period of 25 minutes at 24°C, after which samples were collected and centrifuged for 15 min. at 7000 rpm (Gupta et al., 2010; Tran et al., 2022). The vermicompost solution's initial pH was altered by adding sodium hydroxide or hydrochloric acid at a concentration of 0.0001 moles per liter. Then, after filtration, the supernatants were collected using Whitman 41 filter paper. The samples were kept for inductively coupled plasma optical emission spectrometry (ICP OES) analysis after being maintained with nitric acid drops. As a standard, washing was done using distilled water by oscillatory shaking using mechanical shaker. Equation 1 was used to calculate the response as percentage of crude oil extracted from the washing experiment, as described elsewhere (Wuana et al., 2010).

$$\text{Percentage crude oil removal (\%)} = \frac{C_1 V_1}{C_s M_s} \times 100 \quad (1)$$

Where

C_1 = concentration of crude oil in supernatant (mg/l)

C_s = concentration of crude oil in the soil (mg/kg)

V_1 = the volume of supernatant (litres)

M_s = the dry mass of the soil (kg)

The pH measurements were taken for the solutions prior to washing and the supernatants following washing using mechanical shaker for 25 minutes. All experiments were carried out three times to assure accuracy, and the data obtained were given as averages. Initial concentration of 0.5 g/ml (C_o), 50 mg of contaminated soil was thoroughly combined with 100 ml of distilled water. The absorbance and transmittance were determined using visible range spectrophotometer (model 6100, PYE UNICAM Ltd., England, UK) and the readings taken and values recorded. About 50 g of contaminated soil was mixed with 50 mg, 100 mg, 150 mg, of vermicompost, respectively, in a 500 ml beaker containing 100 ml of distilled water. Beaker was placed in mechanical shaker and shaken at 200 rpm at room temperature of 28°C for 10, 20 and 30 min each. The absorbance and transmittance values were recorded carefully during the experiments. The weight of the adsorbents, and the corresponding equilibrium concentration (C_e) were recorded. Equation 2 and 3 was used to calculate the amount of crude oil absorbed per unit weight of adsorbent for each batch run and it was stated as reported by Uzoije et al. (2011).

$$q_e = \frac{V(C_o - C_e)}{m} \quad (2)$$

The percentage removal is expressed in Equation 3 as:

$$\% \text{ Removal} = \frac{100(C_o - C_e)}{C_o} \quad (3)$$

Where C_o is the initial concentration and C_e is the equilibrium concentration

The mean values were calculated and utilized after triple runs (27) for reproducibility errors. Hundred (100) gram of dried contaminated soil was packed into a plastic column. The soil bulk

density of 0.8 g/cm^3 was achieved by the configuration. The column height was 17.5 cm with the internal diameter of 5 cm. washing fluid were introduced into the soil column at the rate of $5 \text{ ml/min.}(cm^3/min)$. A down-flow mode washing was established by pouring washing solution from the beaker into the soil. After each experiment, the effluent is collected for computing the removal efficiency using equation 3

2.4. ANN model development

The neural fitting toolbox of MATLAB R2017b (MathWorks Inc., Natick, MA, USA) was used to create an artificial neural network (ANN) model of the adsorption process. An input layer (soil solution ratio, pH, duration, and adsorbent dosage), an output layer (percentage removal efficiency), and a concealed layer make up the architecture in Figure 1. The training, validation, and testing data sets were created from the adsorption data set, with respective weights of 70%, 15%, and 15%. *MSE* and *R*² were used as the statistical criterion to evaluate the algorithm's performance in order to choose the best method for the prediction (Nwosu-Obieogu et al., 2022). Using four inputs—contact time, pH, adsorbent dosage, and soil solution ratio—the ANN-based model was created based on the feed-forward, back propagation (BP) algorithms to estimate the removal efficiency of crude oil from crude oil-contaminated soil. With a ratio of 70%, 15%, and 15%, respectively, the one hundred and fifty (150) data sets utilized for the ANN modeling were split at random into three sets (training the network, testing the network, and validating the results).

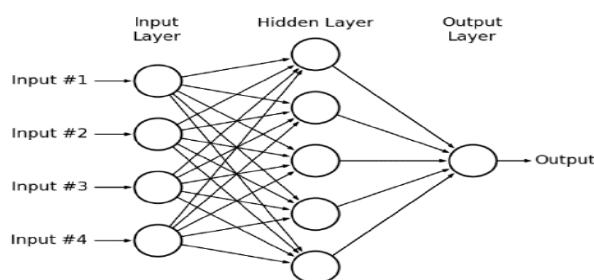


Figure 1: Artificial Neural Network (ANN) Structure

2.5. Model development for ANFIS

By taking into account three input factors (soil solution ratio, pH, time, and adsorbent's dose) and one output variable (% removal efficiency prediction for adsorption of crude oil from contaminated soil using vermicompost), a multi-input single-out (MISO) fuzzy model was created (percentage removal efficiency). The model's architecture is shown in Figure 2, which consists of four layers employing the Takagi-Sugeno fuzzy system: fuzzification, product, rule, defuzzification, and output summation layers (Ausati and Amanollahi, 2016; Ojediran et al., 2020; Rezakazemi et al., 2017).

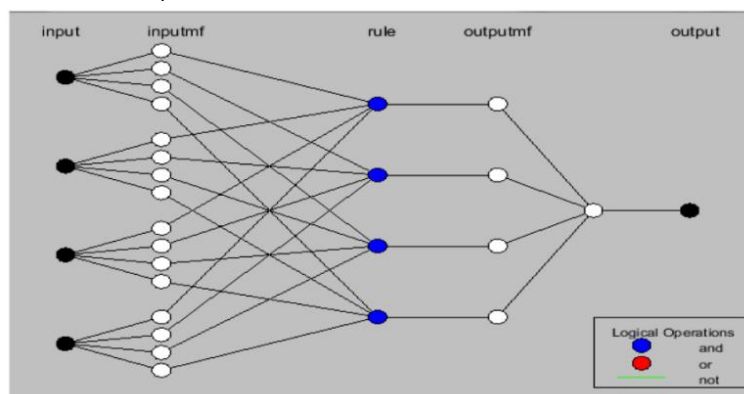


Figure 2: ANFIS structure

2.6. Evaluation of the created models' performance

The following statistical metrics were used to test the model's ability to predict the adsorption process as shown in Equations 4 and 5:

$$\text{(Mean square error) } MSE = \frac{1}{p} \sum_{p=1}^p (d_p - O_p)^2 \quad (4)$$

$$\text{(Coefficient of Determination) } R^2 = 1 - \frac{\sum_{p=1}^p (d_p - O_p)^2}{\sum_{p=1}^p (O_p)^2} \quad (5)$$

d_p and O_p represent the desired and calculated outputs, respectively. The effectiveness of the models is shown by how closely the MSE value to zero (0) and R^2 value to one (1) (Oke et al., 2019).

2.7 Data analysis

In this experiment, the following variables and levels are taken into account: pH, contact time, soil solution ratio, and adsorbent dosage (Table I).

Table I shows the experimental range and the varied levels

Dependent variables	Units	Low level	Medium level	High level
Adsorbent dosage	mg/g	20	35	50
pH		5	7	9
Contact time	min	10	20	30
Soil solution ratio	g/ml	40	70	100

3.0 Results and discussion

3.1 Fourier Transform Infrared Spectroscopy FTIR analysis

FT-IR spectrum of the vermicompost before adsorption (Figure 3) shows that the broad peak at 3693.8 cm^{-1} is ascribed to the O-H stretching due to hydrogen bonding of alcohols and phenolic group or component. The peak at 2053.8 cm^{-1} was attributed to C-H stretching of aliphatic nature-degradation of cellulose, hemicelluloses, lipids, fats functional group or component. The peak at 1423.8 cm^{-1} was attributed to COO stretch of the carboxylic acids. The peaks at 1625.1 cm^{-1} are associated with the C=C aromatic structure which occurred due to mineralization of protein, cellulose, hemicelluloses and evidence of vermicompost maturity. The intense peak at 793.9 cm^{-1} is attributed to the C-O stretch due to carbonate/silica functional group or component. The FT-IR spectrum suggests that the surface functional groups containing O_2 , which include the carboxyl groups and carbonate/silica groups, with higher activation energy influence the adsorption characteristics of vermicompost due to large surface area and pore space size. The FT-IR spectra of the adsorbent (vermicompost) after adsorption are presented (Figure 4), the adsorption of the total petroleum hydrocarbon may have caused the intensity of the broad band at 3697.5 cm^{-1} for O-H bond vibration stretching, and 3697.5 for C=C stretching and 2926.0 for C-O stretching of alcohol to increase, this proves that the total petroleum hydrocarbon bonded with oxygen-containing functionalities on the adsorbent surface of the vermicompost (Gómez-Serrano et al., 1999; Zhou et al., 2007). The result show that there is a slight displacement of the peak in Fourier transform infrared spectroscopy (FT-IR) spectrum of the vermicompost after use. This observation is similar or in agreement with previous studies by Alvarez-Bernal et al. (2006), which suggested that vermicompost had an effect on dissipation of phenanthrene, anthracene and benzo(a)pyrene in soil which are present in crude oil.

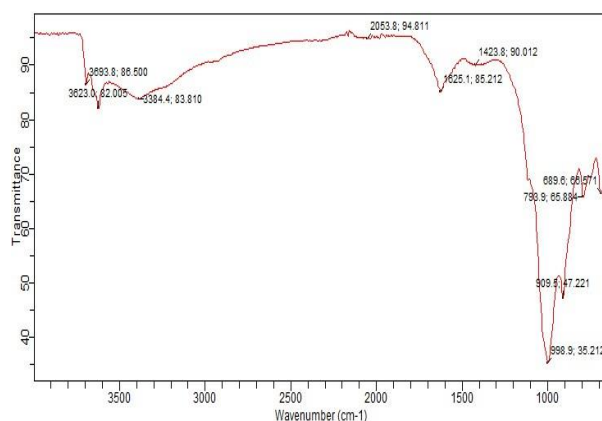


Figure 3: FTIR spectrum for vermicompost before adsorption experiment

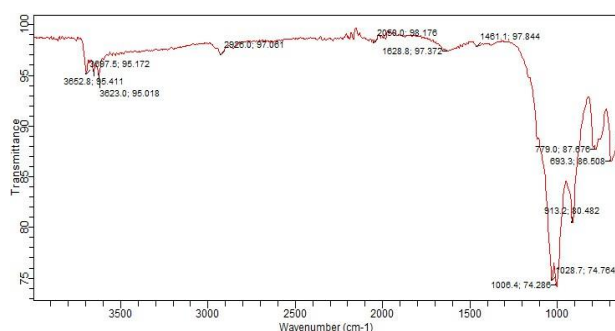


Figure 4: FT-IR spectrum for vermicompost after adsorption experiment

3.2 Scanning electron microscopic (SEM) analysis

SEM images are frequently used to examine the morphological traits and surface properties of adsorbent materials (Nelly and Isacoff, 1982). The Scanning Electron Microscopy (SEM) image of vermicompost before and after adsorption experiment are presented in Figures 5 and 6. The surface morphology of the vermicompost may be due to the presence of hemicellulose/lignin content of the vermicompost and evidence of large surface for adsorption (Medina et al., 2018). The formation of a cluster layers may have resulted from the petroleum hydrocarbon adsorbed on the surface, occupying the cavities of the vermicompost. Wang et al. (2014) reported similar surface morphologies as a result of the adsorption of polycyclic aromatic hydrocarbons by graphene and graphene oxide nanosheets. Uzoije et al. (2011) also noted a similar surface shape for the adsorption of hydrocarbons from industrial wastewater onto a silica mesoporous substance.

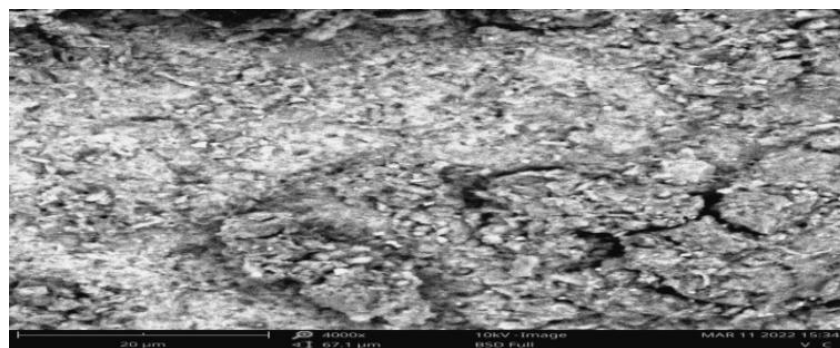


Figure 5: SEM image of vermicompost before adsorption experiment

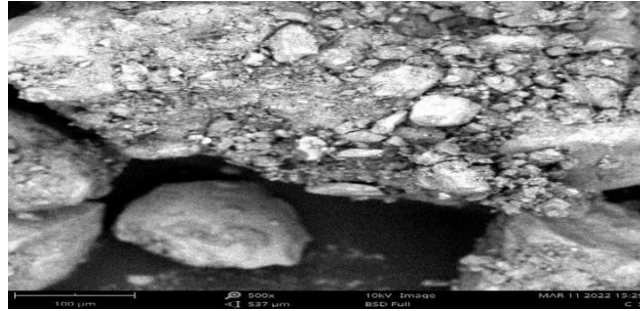


Figure 6: SEM image of vermicompost after adsorption experiment

3.3 ANN simulations

The result of the ANN simulation for batch process is shown in Table 2. Levenberg-Marguardt was the best among the ANN algorithms, having the smallest mean square error (MSE) of 30.538 and the highest coefficient of determination (R2) of 0.9974 for batch process remediation of crude oil contaminated soil. The variation of the MSE with the number of training cycles (epochs) and the Levenberg-Marguardt validation are shown in Figure 7. The training process was terminated when the maximum cycles were reached. The efficiency of the predictive ANN model result for crude oil adsorption using vermicompost is consistent with studies by Onu et al. (2021) and Souza et al. (2018), utilizing modified clay and comparing an ANN and an ANFIS, as well as the mechanistic modeling in eriochrome black-T dye adsorption

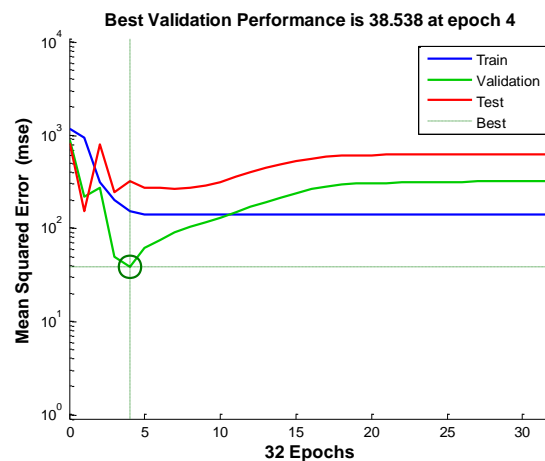


Figure 7: Mean squared error for Levenberg-Marguardt model (ANN) for crude oil removal during batch process remediation

Table 2: Performance of different ANN models in estimating the crude oil removal using vermicompost during batch process

S/No.	Algorithms	MSE	R2
1	Levenberg-Marguardt	30.538	0.99742
2	Bayesian regularization	231.2825	0.08416
3	Scaled conjugate gradient	168.4797	0.58726
4	<i>Trainrp</i>	105.5405	0.88981
5	<i>Traincgf</i>	507.997	0.39210
6	<i>Traincgp</i>	202.082	0.43281
7	<i>Traincgb</i>	242.8735	5.65x10-5
8	<i>Trainbfg</i>	65.0512	0.84293
9	<i>Trainoss</i>	712.742	6.8168x10-4
10	<i>Traingd</i>	363.1146	0.83610
11	<i>Traingdx</i>	121.2558	0.74518
12	<i>Traingdm</i>	621.6924	0.11312

3.4 Artificial Neural Fuzzy Inference System (ANFIS)

Root mean squared error (RMSE) was the parameter utilized by Matlab's Artificial Neural Fuzzy Inference System (ANFIS) function to evaluate the impact of both single and interaction effects on the results of any adsorption tests (Turan and Ozgonenel, 2013). The degree of predictability and reliability of the model is determined by the RMSE number being near to zero (Okolo et al., 2020). The effects of a single input variable and many input variables are shown in Tables 3, 4, and 5 for the lowest ANFIS training error. Table 3 shows the impact of one input variable minimal ANFIS training error with pH having the most significant effect with RMSE of 17.2100 for training the ANFIS model and RMSE of 15.8563 for testing the ANFIS model. Table 4 show the impact of two inputs variable with contact time and pH having the most significant effect with RMSE of 12.7478 for training the ANFIS model and RMSE of 17.7019 for testing the ANFIS model for the removal crude oil from crude oil contaminated soil using vermicompost during batch process remediation. Table 5 shows that pH had the most significant effect with RMSE of 17.21 for training the ANFIS model and RMSE of 15.8463 for testing the ANFIS model for the removal of crude oil from contaminated soil using vermicompost during batch process remediation. On the other hand, contact time/pH/Adsorbent dosage impacted most with RMSE of 11.2811 for training the ANFIS model and pH/Soil solution ratio/Contact time with RMSE of 11.6687 for testing the ANFIS model in Table 5. These findings demonstrate that when utilizing vermicompost in a batch method for remediation of crude oil-contaminated soil, the variables pH, contact time, Soil solution ratio, and Adsorbent dosage have a substantial impact on the removal of crude oil. This finding is consistent with and supported by earlier investigations' assertions by Contreras-Ramos et al. (2008) and Zheng and Obbard (2002).

Table 3: One-input variable of ANFIS (exhaustive) crude oil removal using vermicompost during batch process remediation.

S/No.	No. of input	Input variable	Training (RMSE)	Testing (RMSE)
1	1	Contact time	19.0907	18.2413
2	1	Ph	17.2100	15.8463
3	1	Adsorbent dosage	19.7671	21.0202
4	1	Soil solution ratio	20.0510	17.9668

Table 4: Two-input variable of ANFIS (exhaustive) crude oil removal using vermicompost during batch process remediation

S/No.	No. of inputs	Input variable	Training (MSE)	Testing (MSE)
1	2	Contact time/pH	12.7478	17.7019
2	2	Contact time/Adsorbent dosage	18.3199	20.2402
3	2	Contact time/Soil solution ratio	17.6990	28.6980
4	2	pH/Adsorbent dosage	15.6837	19.7244
5	2	pH/Soil solution ratio	16.0167	37.9853
6	2	Adsorbent dosage/Soil solution ratio	19.5717	18.4994

Table 5: Three-input variables ANFIS (exhaustive search) for crude oil removal using vermicompost during batch process remediation

S/No.	No. of inputs	Input variables	Training (MSE)	Testing (MSE)
1.	3	Contact time/pH/Adsorbent dosage	11.2811	60.8264
2.	3	pH/Adsorbent dosage/Soil solution ratio	14.2298	18.8270
3.	3	pH/Soil solution ratio/Contact time	11.6687	11.6687
4	3	Contact time/Soil solution ratio/Adsorbent dosage	16.3237	24.3629

3.5 Comparative Analysis of RSM, ANN and ANFIS Modelling of Crude Oil Adsorption Using Vermicompost (Adsorbent) During Column and Batch Process Remediation

This result in Table 6 compared RSM, ANN and ANFIS results to evaluate the model's predicting ability for crude oil removal from crude oil contaminated soil using statistical metrics such as coefficient of determination (R^2) and root mean squared error (RMSE) during batch and column process remediation. The correlation coefficient (R^2) and the mean squared error (MSE) were used to validate the model predictiveness. Table 6 summarizes the ANFIS results of different experimental process. Column process gave a prediction of R^2 (0.9978) and MSE (2.7840) during linear model function and R^2 (0.9864) and MSE (3.63284) was obtained during constant model function. Batch process gave a prediction of R^2 (0.7115) and MSE (10.1778) during linear model function and R^2 (0.7115) and MSE (10.1798) was obtained during constant model function. The coefficient of determination (R^2) for ANN as 0.9974 and 0.9852 for batch and column process respectively, showing the agreement between experimental and predicted results. The coefficient of determination R^2 for RSM as 0.9712 and 0.9614 for batch and column process respectively, which also show an agreement between experimental and predicted results. The coefficient of determination for ANFIS as 0.7115 and 0.9978 respectively for batch and column process respectively. These results showed the capability of the models in predicting crude oil removal from contaminated soil using vermicompost (adsorbent). However, the coefficient of determination of ANN is higher than that of RSM and ANFIS for batch process; while the coefficient of determination of ANFIS is higher than that of RSM and ANN for the column process remediation. This is similar to the studies of Zheng and Obbard (2002).

Table 6: RSM, ANN and ANFIS Modelling of Crude Oil Adsorption Using Vermicompost (Adsorbent) During Column and Batch Process Remediation

S/N	Models	Batch process		Column process	
		R^2	RMSE	R^2	RMSE
1	RSM	0.9712	2.4791	0.9614	3.2410
2	ANN	0.9974	5.5261	0.9852	1.6624
3	ANFIS	0.7115	3.1903	0.9978	1.6685

3.6 ANFIS simulation

The best ANFIS prediction for crude oil adsorption using vermicompost was simulated at different input and output from the laboratory experimental data using 4,000 data sets. Batch process gave a prediction of R^2 (0.7115) and MSE (10.1778) during linear model function and R^2 (0.7115) and MSE (10.1798) was obtained during constant model function. The result shows that the ANFIS linear model is capable of predicting adsorption of crude-oil using vermicompost with high precision. The obtained result is similar to Souza *et al.* (2018).

4.0 Conclusion

Vermicompost's impact on crude-oil polluted soil was studied using a batch experimental process to determine the level of remediation. Artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) could be used to predict the removal of crude oil from polluted soil. Influencing parameters which include adsorbent dosage, soil solution ratio, contact time and pH were studied. ANN and ANFIS were evaluated using the coefficient of determination (R^2) and mean square error (MSE). Optimization of the experimental factors carried out using numerical optimization techniques by applying desirability function method produce the highest removal efficiency of 98.9% at adsorbent dosage of 34.53 grams, adsorbate concentration of 69.11 (g/ml), contact time of 25.96 (min), and pH value of 7.71 respectively. ANN simulation of the batch process show that Levenberg-Marguardt was the best among the ANN algorithms, having the smallest mean square error (MSE) of 30.538 and the highest coefficient of determination (R^2) of 0.9974 for batch process remediation of crude oil contaminated soil. Column process gave a prediction of R^2 (0.9978) and MSE (2.7840) during

linear model function and R^2 (0.9864) and MSE (3.63284) was obtained during constant model function. Batch process gave a prediction of R^2 (0.7115) and MSE (10.1778) during linear model function and R^2 (0.7115) and MSE (10.1798) was obtained during constant model function. The coefficient of determination (R^2) for ANN as (0.9974) for batch. Showing the agreement between experimental and predicted results. The coefficient of determination for ANFIS was (0.7115) for batch process. This study shows the capability of machine learning models in predicting crude oil removal from contaminated soil using Vermicompost. It is therefore certain that ANN and ANFIS are promising forecasting methods that can be used to estimate the removal of crude oil from contaminated soil using Vermicompost.

References

Adedokun, OM. and Ataga, AE. 2006. Effects of crude oil and oil products on growth of some edible mushrooms. *Journal of Applied Sciences and Environmental Management*, 10(2): 14-18.

Adhikary, S. 2012. Vermicompost, the story of organic gold: A review. *Agricultural Science*, 3(7): 905.-907.

Agatonovic-Kustrin, S. and Beresford, R. 2000. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of Pharmaceutical and Biomedical Analysis*, 22(5): 717–727.

Alvarez-Bernal, D., Garcia-Diaz, EL., Contreras-Ramos, SM. and Dendooven, L. 2006. Dissipation of polycyclic aromatic hydrocarbons from soil added with manure or vermicompost. *Chemosphere*, 65(9): 1642–1651.

Amin, MM., Rahimi, A., Bina, B., Nourmoradi, H., Hassanvand, MS., Mohammadi-Moghadam, F., Norouzi, S. and Heidari, M. 2017. Biodegradation of n-hexane as single pollutant and in a mixture with BTEX in a scoria/compost-based biofilter. *Process Safety and Environmental Protection*, 107: 508–517.

Ani, KA. and Agu, CM. 2022. Predictive comparison and assessment of ANFIS and ANN, as efficient tools in modeling degradation of total petroleum hydrocarbon (TPH). *Cleaner Waste Systems*, 3: 100052.

Asadu, CO., Ekwueme, BN., Onu, CE., Onah, TO., Ike, IS. and Ezema, CA. 2022. Modelling and optimization of crude oil removal from surface water via organic acid functionalized biomass using machine learning approach. *Arabian Journal of Chemistry*, 8(3):104-125.

Ausati, S. and Amanollahi, J. 2016. Assessing the accuracy of ANFIS, EEMD-GRNN, PCR, and MLR models in predicting PM_{2.5}. *Atmospheric Environment*, 142: 465–474.

Chen, M., Xu, P., Zeng, G., Yang, C., Huang, D. and Zhang, J. 2015. Bioremediation of soils contaminated with polycyclic aromatic hydrocarbons, petroleum, pesticides, chlorophenols and heavy metals by composting: Applications, microbes and future research needs. *Biotechnology Advances*, 33(6): 745–755.

Contreras-Ramos, SM., Álvarez-Bernal, D. and Dendooven, L. 2008. Removal of polycyclic aromatic hydrocarbons from soil amended with biosolid or vermicompost in the presence of earthworms (*Eisenia fetida*). *Soil Biology and Biochemistry*, 40(7): 1954–1959. <https://doi.org/10.1016/j.soilbio.2008.04.009>

Daka, ER. and Ekweozor, IKE. 2004. Effect of size on the acute toxicity of crude Oil to the mangrove oyster, *Carasostrea gasar*. *International Journal of Environment and Pollution*. 23(14): 272-278.

de Souza Pohren, R., Rocha, JAV., Horn, KA. and Vargas, VMF. 2019. Bioremediation of soils contaminated by PAHs: Mutagenicity as a tool to validate environmental quality. *Chemosphere*, 214: 659–668.

Dores-Silva, PR., Cotta, JA., Landgraf, MD. and Rezende, MO. 2019. The application of the vermicomposting process in the bioremediation of diesel contaminated soils. *Journal of Environmental Science and Health, Part B*, 54(7): 598–604.

García-Díaz, C., Ponce-Noyola, MT., Esparza-García, F., Rivera-Orduña, F. and Barrera-Cortés, J. 2013. PAH removal of high molecular weight by characterized bacterial strains from different organic sources. *International Biodeterioration and Biodegradation*, 85: 311–322.

Gighi, JG., Tanee, FBG. and Albert, E. 2012. Post-impact soil assessments of crude oil spill site in kpean community in Khana LGA (Ogoni) of rivers state, Nigeria. *Journal of Science*, 8(2):109–120.

Gómez-Serrano, V., Piriz-Almeida, F., Durán-Valle, CJ. and Pastor-Villegas, J. 1999. Formation of oxygen structures by air activation. A study by FT-IR spectroscopy. *Carbon*, 37(10): 1517–1528

Hutchful, E. 1985. Texaco's Funiwa-5 Oil Well Blow-out, Rivers State, Nigeria. *Journal of African Marxists*, 7: 51–62.

Ite, AE., Ibok, UJ., Ite, MU. and Petters, SW. 2013. Petroleum exploration and production: Past and present environmental issues in the Nigeria's Niger Delta. *American Journal of Environmental Protection*, 1(4): 78–90.

Jack, IR., Fekarurhobo, GK., Igwe, FU. and Okorosaye-Orubite, K. 2005. Determination of total hydrocarbons levels in some marine organisms from some towns within the Rivers State of Nigeria. *Journal of Applied Sciences and Environmental Management*, 9(3): 59–61.

Kästner, M. and Miltner, A. 2016. Application of compost for effective bioremediation of organic contaminants and pollutants in soil. *Applied Microbiology and Biotechnology*, 100(8): 3433–3449.

Kose, E. 2008. Modelling of colour perception of different age groups using artificial neural networks. *Expert Systems with Applications*, 34(3): 2129–2139.

Lim, SL., Wu, TY., Lim, PN. and Shak, KPY. 2015. The use of vermicompost in organic farming: Overview, effects on soil and economics. *Journal of the Science of Food and Agriculture*, 95(6): 1143–1156.

Maretto, M., Vignola, R., Williams, CD., Bagatin, R., Latini, A. and Papini, MP. 2015. Adsorption of hydrocarbons from industrial wastewater onto a silica mesoporous material: Structural and thermal study. *Microporous and Mesoporous Materials*, 203: 139–150.

Medina, R., Gara, PMD., Fernández-González, AJ., Rosso, JA. and Del Panno, MT. 2018. Remediation of a soil chronically contaminated with hydrocarbons through persulfate oxidation and bioremediation. *Science of the Total Environment*, 618: 518–530.

Mohammadi-Moghadam, F., Khodadadi, R., Sedehi, M. and Arbabi, M. 2022. Bioremediation of Polycyclic Aromatic Hydrocarbons in Contaminated Soils Using Vermicompost. *International Journal of Chemical Engineering*, 12(6): 125-137.

Nasr, M., Mahmoud, AED., Fawzy, M. and Radwan, A. 2017. Artificial intelligence modeling of cadmium (II) biosorption using rice straw. *Applied Water Science*, 7(2): 823–831.

Nelly, JW. and Isacoff, EG. 1982. Carbonaceous Adsorbents for the Treatment of Ground and Surface Water. Marcel Dekker, New York.

Nwosu-Obieogu, K., Dzarma, GW., Ehiomogbe, P., Ugwuodo, CB. and Chiemenem, LI. 2022. Textile wastewater heavy metal removal using *Luffa cylindrica* activated carbon: An ANN and ANFIS predictive model evaluation. *Applied Water Science*, 12(3): 1–11.

Ojediran, JO., Okonkwo, CE., Adeyi, AJ., Adeyi, O., Olaniran, AF., George, NE. and Olayanju, AT. 2020. Drying characteristics of yam slices (*Dioscorea rotundata*) in a convective hot air dryer: Application of ANFIS in the prediction of drying kinetics. *Heliyon*, 6(3): e03555.

Oke, EO., Araromi, DO., Jimoda, LA. and Adetayo Adeniran, J. 2019. Kinetics and neuro-fuzzy soft computing modelling of river turbid water coag-flocculation using mango (*Mangifera indica*) kernel coagulant. *Chemical Engineering Communications*, 206(2): 254–267.

Okolo, BI., Oke, EO., Agu, CM., Adeyi, O., Nwosu-Obieogu, K. and Akatobi, KN. 2020. Adsorption of lead (II) from aqueous solution using Africa elemi seed, mucuna shell and oyster shell as adsorbents and optimization using Box–Behnken design. *Applied Water Science*, 10(8): 1–23.

Onu, CE., Nwabanne, JT., Ohale, PE., and Asadu, CO. 2021a. Comparative analysis of RSM, ANN and ANFIS and the mechanistic modeling in eriochrome black-T dye adsorption using modified clay. *South African Journal of Chemical Engineering*, 36: 24–42.

Onu, CE., Nwabanne, JT., Ohale, PE. and Asadu, CO. 2021b. Comparative analysis of RSM, ANN and ANFIS and the mechanistic modeling in eriochrome black-T dye adsorption using modified clay. *South African Journal of Chemical Engineering*, 36: 24–42.

Ordinoha, B. and Brisibe, S. 2013. The human health implications of crude oil spills in the Niger delta, Nigeria: An interpretation of published studies. *Nigerian Medical Journal*, 54(1): 10.

Rajiv, KS., Sunita, A., Krunal, C., Vinod, C. and Brijal Kiranbhai, S. 2010. Vermiculture technology: Reviving the dreams of Sir Charles Darwin for scientific use of earthworms in sustainable development programs. *Technology and Investment*, 19(3):167-175.

Rein, A., Adam, IK., Miltner, A., Brumme, K., Kästner, M. and Trapp, S. 2016. Impact of bacterial activity on turnover of insoluble hydrophobic substrates (phenanthrene and pyrene) Model simulations for prediction of bioremediation success. *Journal of Hazardous Materials*, 306: 105–114.

Rezakazemi, M., Dashti, A., Asghari, M. and Shirazian, S. 2017. H₂-selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS. *International Journal of Hydrogen Energy*, 42(22): 15211–15225.

Rivera, EC., Rabelo, SC., dos Reis Garcia, D., Filho, RM. and da Costa, AC. 2010. Enzymatic hydrolysis of sugarcane bagasse for bioethanol production: Determining optimal enzyme loading using neural networks. *Journal of Chemical Technology and Biotechnology*, 85(7): 983–992.

Roy, K., Mukherjee, A. and Jana, DK. 2019. Prediction of maximum oil-yield from almond seed in a chemical industry: A novel type-2 fuzzy logic approach. *South African Journal of Chemical Engineering*, 29(1): 1–9.

Ryan, J., Estefan, G. and Rashid, A. 2001. *Soil and Plant Analysis Laboratory Manual. Soil and plant analysis lab manual. 2nd ed.* International Center for Agricultural Research in the Dryland Areas (ICARDA), Aleppo, Syria. National Agricultural Research Center, Islamabad, Pakistan.

Sonwani, RK., Giri, BS., Geed, SR., Sharma, A., Singh, RS. and Rai, BN. 2018. Combination of UV-Fenton oxidation process with biological technique for treatment of polycyclic aromatic hydrocarbons using *Pseudomonas pseudoalcaligenes* NRSS3 isolated from petroleum

contaminated site. *Journal Scientific Frontiers*, 7(2): 79-98.

Souza, PR., Dotto, GL. and Salau, NPG. 2018a. Artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS) modelling for nickel adsorption onto agro-wastes and commercial activated carbon. *Journal of Environmental Chemical Engineering*, 6(6): 7152–7160.

Souza, PR., Dotto, GL. and Salau, NPG. 2018b. Artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS) modelling for nickel adsorption onto agro-wastes and commercial activated carbon. *Journal of Environmental Chemical Engineering*, 6(6): 7152–7160.

Thapa, B., Kc, AK. and Ghimire, A. 2012. A review on bioremediation of petroleum hydrocarbon contaminants in soil. *Kathmandu University Journal of Science, Engineering and Technology*, 8(1): 164–170.

Turan, NG. and Ozgonenel, O. 2013. The design and implementation of adsorptive removal of Cu (II) from leachate using ANFIS. *The Scientific World Journal*, 8(4): 98-109.

Uzoije, AP., Onunkwo, AA. and Egwuonwu, N. 2011. Crude oil sorption onto groundnut shell activated carbon: Kinetic and isotherm studies. *Research Journal of Environmental and Earth Sciences*, 3(5): 555–563.

Wang, J., Chen, Z. and Chen, B. 2014. Adsorption of polycyclic aromatic hydrocarbons by graphene and graphene oxide nanosheets. *Environmental Science and Technology*, 48(9): 4817–4825.

Wang, K., Zhang, J., Zhu, Z., Huang, H., Li, T., He, Z., Yang, X. and Alva, A. 2012. Pig manure vermicompost (PMVC) can improve phytoremediation of Cd and PAHs co-contaminated soil by *Sedum alfredii*. *Journal of Soils and Sediments*, 12(7): 1089–1099.

Yatoo, AM., Ali, M., Baba, ZA. and Hassan, B. 2021. Sustainable management of diseases and pests in crops by vermicompost and vermicompost tea. A review. *Agronomy for Sustainable Development*, 41(1): 1–26.

Yilmaz, I. and Yuksek, G. 2009. Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. *International Journal of Rock Mechanics and Mining Sciences*, 46(4): 803–810.

Zheng, Z. and Obbard, JP. 2002. Polycyclic aromatic hydrocarbon removal from soil by surfactant solubilization and *Phanerochaete chrysosporium* oxidation. *Journal of Environmental Quality*, 31(6): 1842–1847.

Zhou, JH., Sui, ZJ., Zhu, J., Li, P., Chen, D., Dai, YC., and Yuan, WK. 2007. Characterization of surface oxygen complexes on carbon nanofibers by TPD, XPS and FT-IR. *Carbon*, 45(4): 785–796.