Communications in Mathematics and Applications
Vol. 15, No. 5, pp. 1443–1457, 2024
ISSN 0975-8607 (online); 0976-5905 (print)
Published by RGN Publications
DOI: 10.26713/cma.v15i5.2903

http://www.rgnpublications.com

Research Article

Application of Adaptive Neuro-Fuzzy Inference System (ANFIS) For Optimizing Nano-Biochar Application in Soil Remediation Projects in Chas

Mukesh Kumar Sinha*[1,2] and Rajesh Kumar Tiwari[1]

[1] *University Department of Mathematics, Binod Bihari Mahto Koyalanchal University, Dhanbad 828103, Jharkhand, India*
[2] *Guru Gobind Singh Educational Society's Technical Campus (affiliated to Jharkhand University of Technology, Ranchi), Chas, Bokaro 827013, Jharkhand, India*
***Corresponding author:** sinhamukesh.dazy@gmail.com

Received: October 8, 2024 **Accepted:** December 3, 2024

Abstract. *The use of the Adaptive Neuro-Fuzzy Inference System* (ANFIS) is investigated into this work for optimizing nano-biochar application in soil remediation projects in Chas, Bokaro, Jharkhand, India. The research addresses the critical need for effective soil remediation techniques in areas affected by industrial pollution and agricultural intensification. By leveraging ANFIS, an intelligent hybrid system that blends neural networks with fuzzy logic, we aim to enhance the precision and efficiency of nano-biochar application in soil remediation efforts. The study encompasses extensive field experiments, laboratory analyses, and computational modeling to develop a well ANFIS model for forecast optimal nano-biochar dosages based on various soil parameters and contaminant levels. Results demonstrate the superior performance of ANFIS in optimizing nano-biochar application compared to conventional methods, leading to improved soil quality indicators and reduced remediation time. This research contributes to the advancement of sustainable soil management practices and provides a valuable tool for environmental practitioners and policymakers in Chas and similar regions facing soil contamination challenges.

Keywords. ANFIS, Nano-biochar, Soil remediation, Chas, Optimization, Environmental management

Mathematics Subject Classification (2020). 93C42, 62P30, 68T05

1. Introduction

Soil contamination presents a significant environmental challenge globally, with far-reaching implications for ecosystem health, agricultural productivity, and human well-being. Recently, the city of Chas, which is located in the Bokaro district of Jharkhand, India, has faced escalating soil pollution issues due to rapid industrialization and intensive agricultural practices. The pollution of soil with heavy metals, organic pollutants, and other harmful substances has raised important discussion about food safety, water quality, and public health in the region (Alloway [3]).

In response to these challenges, innovative soil remediation techniques have emerged as crucial tools for restoring contaminated soils to their natural state. Among these techniques, the application of nano-biochar has shown promising results in enhancing soil quality and facilitating the removal of various contaminants. Carbonaceous material known as "nano-biochar" is created when biomass is pyrolyzed at the nanoscale, show different properties that produce highly effective in soil remediation projects. Among these characteristics are high surface area, porosity, and reactivity, which contribute to better water retention and soil structure, and enhanced adsorption of pollutants (Tan *et al*. [17]).

However, the effectiveness of nano-biochar application in soil remediation depends heavily on several variables, including soil characteristics, contaminant types and concentrations, environmental conditions, and application methods. Determining the optimal dosage and application strategy for nano-biochar in diverse soil environments remains a significant challenge for environmental practitioners and researchers (Zhang and Gao [20]).

In order to address this issue, this paper suggests the use of the *Adaptive Neuro-Fuzzy Inference System* (ANFIS) for optimizing nano-biochar application in soil remediation projects in Chas. ANFIS, a hybrid expert system that blends the capacity for learning of artificial neural networks with the reasoning power of fuzzy logic, offer a strong strategy to modeling complex, nonlinear relationships in environmental systems (Jang [5]).

The following are the main goals of this research work:

(i) To develop a comprehensive ANFIS model for predicting optimal nano-biochar dosages based on soil parameters and contaminant levels in Chas.

(ii) To assess how well the ANFIS model performs in compared with traditional optimization techniques for nano-biochar application.

(iii) To assess the impact of ANFIS-optimized nano-biochar application on soil quality indicators and remediation efficiency.

(iv) To provide guidelines and recommendations for the implementation of ANFIS-based optimization in soil remediation projects using nano-biochar.

2. Literature Review

2.1 Soil Contamination in Chas

Chas, a rapidly developing industrial town in the Bokaro district of Jharkhand, India, has experienced significant environmental challenges in the last few years due to accelerated industrialization and agricultural intensification. The region's soil contamination issues come from a variety of sources, such as industrial effluents, improper waste disposal, and the excessive use of agrochemicals. Several studies have documented the extent and nature of soil contamination in Chas and similar region of India. Sharma and Raju [16] conducted a comprehensive survey of heavy metal contamination in agricultural soils around in Industrial areas of Jharkhand, revealing elevated levels of lead (Pb), cadmium (Cd), and chromium (Cr) in multiple sampling sites. The study attributed these high concentrations to the proximity of industrial zones and the long-term application of contaminated irrigation water. Kuppusamy *et al*. [8] investigated the impact of organic pollutants on soil quality in urban and peri-urban areas of India, focusing on *Polycyclic Aromatic Hydrocarbons* (PAHs) and pesticide residues. Their findings indicated a significant accumulation of these contaminants of soil samples obtained from peri-urban and urban areas, raising concerns about potential food chain contamination and associated health risks. The consequences of soil contamination extend beyond environmental degradation. Setia *et al*. [15] examined the socio-economic impacts of soil pollution on local communities, highlighting reduced agricultural productivity, declining property values, and increased healthcare costs as major concerns among residents.

The key soil contaminants identified in Chas and their primary sources based on recent studies are summarized as shown in Table 1.

Table 1. Major soil contaminants and their sources in Chas

Contaminant type	Specific contaminants	Primary sources
Heavy metals	Lead (Pb), Cadmium (Cd), Chromium (Cr), Arsenic (As), Mercury (Hg)	Industrial effluents, vehicular emissions, smelting operations
Organic pollutants	Polycyclic Aromatic Hydrocarbons (PAHs), Pesticide residues, Polychlorinated Biphenyls (PCBs)	Industrial processes, agricultural runoff, waste incineration
Nutrients	Excess Nitrogen (N), Phosphorus (P)	Over-application of fertilizers, animal waste
Petroleum hydrocarbons	Benzene, Toluene, Ethylbenzene, Xylene (BTEX)	Oil spills, leaking underground storage tanks
Microplastics	Various polymer types	Industrial waste, urban runoff, improper waste disposal

2.2 Nano-Biochar: Properties and Applications in Soil Remediation

Nano-biochar has become a powerful tool in soil remediation because its distinct physicochemical characteristics and versatile applications. This section explores the characteristics of nano-biochar and its potential for addressing soil contamination issues.

2.2.1 Properties of Nano-Biochar

Nano-biochar is produced through pyrolysis of biomass materials when the temperatures is high (300-700 °C) under low oxygen conditions, followed by processing to achieve nanoscale dimensions (typically < 100 nm). The nanoscale structure of this material confers several advantageous properties for soil remediation:

(i) *High Surface Area*: Nano-biochar exhibits an exceptionally high surface area-to-volume ratio, often exceeding 1000 m^2/g. This characteristic increases the adsorption capability of it for various contaminants (Ahmad *et al*. [1]).

(ii) *Porosity*: The nanoscale pores in biochar offers many different fields for contaminants and facilitate the retention of water and nutrients in the soil (Qian *et al*. [14]).

(iii) *Surface Functionality*: Nano-biochar contains various functional groups (e.g., carboxyl, hydroxyl, phenolic) that contribute to its reactivity and ability to interact with soil components and contaminants (Lehmann *et al*. [9]).

(iv) *Stability*: The carbonaceous structure of nano-biochar imparts high stability in soil environments, allowing for long-term benefits in soil remediation projects (Manya *et al*. [10]).

The key properties of nano-biochar in comparison to conventional biochar and activated carbon are summarized as shown in Table 2.

Table 2. Comparison of properties: nano-biochar, conventional biochar, and activated carbon

Property	Nano-biochar	Conventional biochar	Activated carbon
Particle size	< 100 nm	> 1 μm	Variable (μm to mm)
Surface area	500-2000 m^2/g	50-500 m^2/g	500-2000 m^2/g
Pore volume	0.6-2.0 cm^3/g	0.1-0.5 cm^3/g	0.5-1.5 cm^3/g
Cation exchange capacity	20-50 cmol/kg	5-30 cmol/kg	2-5 cmol/kg
Carbon content	60-90%	50-80%	80-95%
Stability in soil	High	Moderate to high	High
Production temperature	300-700 °C	300-700 °C	600-1200 °C

2.2.2 Applications in Soil Remediation

The unique properties of nano-biochar make it particularly effective in various soil remediation applications:

(i) *Heavy Metal Immobilization*: Nano-biochar has demonstrated superior capacity for absorbing and immobilizing heavy metals in contaminated soils. Bian *et al*. [4] reported significant reductions in the bioavailability of lead (Pb) and cadmium (Cd) in agricultural soils treated with nano-biochar derived from rice straw.

(ii) *Organic Pollutant Degradation*: The large surface area together with catalytic properties of nano-biochar facilitate the adsorption and degradation of organic contaminants. A study by Zhang *et al*. [21] showed enhanced degradation of polycyclic aromatic hydrocarbons (PAHs) in nano-biochar-amended soils compared to untreated controls.

(iii) *Nutrient Management*: Nano-biochar can help mitigate nutrient pollution by retaining excess nutrients and slowly releasing them for plant uptake. Yao *et al*. [19] demonstrated improved nitrogen use efficiency and reduced nitrate leaching in nano- biochar-treated agricultural soils.

(iv) *Soil Structure Improvement*: The application of nano-biochar has been shown to enhance soil aggregation, water retention, and microbial activity. These improvements contribute to overall soil health and resilience against contamination (Ouyang *et al*. [13]).

2.3 Adaptive Neuro-Fuzzy Inference System (ANFIS): Principles and Environmental Applications

The *Adaptive Neuro-Fuzzy Inference System* (ANFIS) represents a powerful creative intelligent system that blends the learning capabilities of synthetic neural networks equipped with the reasoning power of fuzzy logic. This section explores the fundamental principles of ANFIS and its applications in environmental modeling and optimization.

2.3.1 Principles of ANFIS

ANFIS, first introduced by Jang [5], is founded on the Takagi-Sugeno fuzzy logic system. It integrates the adaptive learning algorithms of neural networks with the interpretability of fuzzy logic systems. The key components and principles of ANFIS include:

(i) *Fuzzy Inference System* (*FIS*): ANFIS utilizes a fuzzy logic system to map input variables to output variables using if-then rules and fuzzy logic (Jang *et al*. [6]).

(ii) *Adaptive Learning*: The system utilizes learning techniques for neural networks to adjust the role of membership and parameters based on input-output data (Nayak *et al*. [12]).

(iii) *Layered Structure*: ANFIS typically consists of five layers: fuzzification, rule base, normalization, defuzzification, and output (Jang [5]).

(iv) *Hybrid Learning Algorithm*: For parameter efficiency, ANFIS combines gradient descent backpropagation techniques with least-squares approximation (Jang *et al*. [6]).

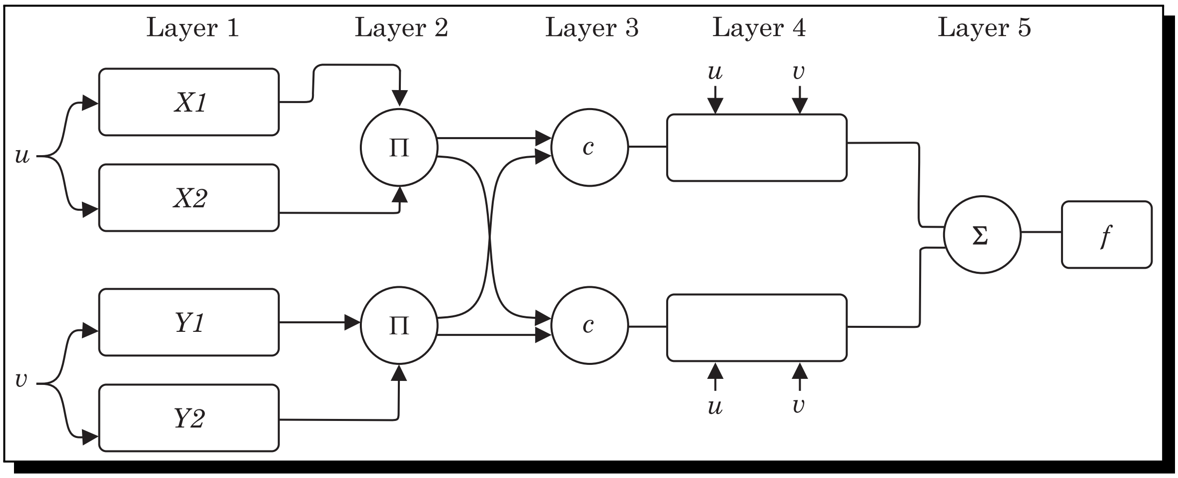

Figure 1. Typical architecture of an ANFIS model [5]

2.3.2 Environmental Applications of ANFIS

ANFIS has found widespread application in environmental modeling and optimization because of its capacity to handle complex, nonlinear relationships and incorporate expert knowledge. Some key environmental applications include:

(i) *Water Quality Prediction*: Kisi and Ay [7] applied ANFIS to predict dissolved oxygen concentrations in rivers, demonstrating superior performance compared to traditional regression models.

(ii) *Air Pollution Forecasting*: Taylan [18] developed an ANFIS model for forecasting PM10 concentrations in urban areas, achieving high accuracy in predicting daily pollution levels.

(iii) *Soil Erosion Modeling*: Ahmadlou *et al*. [2] used ANFIS to calculate soil erosion rates in relation to several environmental parameters, offering insightful information about land management techniques.

(iv) *Renewable Energy Optimization*: Mellit and Kalogirou [11] applied ANFIS for sizing photovoltaic systems, optimizing energy production based on environmental and technical parameters.

The successful application of ANFIS in various environmental domains suggests its potential for optimizing nano-biochar application in soil remediation projects. By leveraging the adaptive learning capabilities of ANFIS, it is feasible to create models that provide precise predictions. Optimal nano-biochar dosages based on soil characteristics, contaminant levels, and environmental conditions.

The complex nature of soil contamination in Chas, characterized by the presence of multiple contaminants from diverse sources, underscores the need for innovative and effective remediation strategies. The application of nano-biochar, optimized through advanced computational techniques such as ANFIS, presents a promising approach to addressing these multifaceted soil pollution challenges.

3. Materials and Methods

This section details the methodological approach employed in this study, encompassing field experiments, laboratory analyses, and the development and validation of the ANFIS model for optimizing nano-biochar application in soil remediation projects in Chas.

3.1 Study Area

The research was carried out in Chas, a city located in the Bokaro district of Jharkhand, India (23.63 °N, 86.17 °E). Chas is characterized by a tropical savanna climate with an average annual temperature of 26 °C and precipitation of 1,400 mm. The area has rapidly become more industrialized and urbanization over the previous few decades, leading to significant soil contamination issues.

Five research location were chosen inside Chas, representing different land-use types and contamination levels:

(i) *Industrial Zone* (IZ): Located near a cluster of manufacturing facilities.

(ii) *Agricultural Land* (AL): Intensively cultivated area with a history of agrochemical use.

(iii) *Urban Residential Area* (UR): Densely populated residential zone.

(iv) *Peri-urban Open Space* (PO): Undeveloped land at the city's periphery.

(v) *Remediated Control Site* (RC): Previously contaminated site that underwent conventional. remediation

3.2 Soil Sampling and Characterization

Samples of soil were gathered from each study site following a stratified random sampling approach. At each site, 20 subsamples were gathered from the top 0-20 cm soil layer and combined to form a composite sample. Three times over, this process was completed, at each site to account for spatial variability.

The samples of soil collected were crushed, air-dried, and sieved through a 2 mm mesh for subsequent analyses. The following characteristics within the soil were found using standard methods:

- Particle size distribution (hydrometer method)
- pH (1:2.5 soil: water suspension)
- Electrical conductivity (EC) (1:5 soil: water extract)
- Organic matter content (Walkley-Black method)
- Cation exchange capacity (CEC) (ammonium acetate method)
- Total nitrogen (Kjeldahl method)
- Available phosphorus (Olsen method)
- Available potassium (ammonium acetate extraction)
- Heavy metal concentrations (Pb, Cd, Cr, As, Hg) (acid digestion followed by ICP-MS analysis)
- Polycyclic aromatic hydrocarbons (PAHs) (solvent extraction followed by GC-MS analysis)

The mean values (± standard deviation) of key soil properties across the five study sites are shown in Table 3.

Table 3. Mean values (± SD) of soil characteristics throughout study sites in Chas

Soil property	Industrial Zone (IZ)	Agricultural Land (AL)	Urban Residential (UR)	Peri-urban Open Space (PO)	Remediated Control (RC)
pH	6.2 ± 0.3	6.8 ± 0.2	7.1 ± 0.4	6.5 ± 0.3	6.9 ± 0.2
EC (dS/m)	0.98 ± 0.12	0.45 ± 0.08	0.62 ± 0.09	0.31 ± 0.05	0.52 ± 0.07
Organic matter (%)	1.8 ± 0.4	2.5 ± 0.5	2.1 ± 0.3	1.5 ± 0.2	2.3 ± 0.4
CEC (cmol/kg)	12.5 ± 1.8	15.3 ± 2.1	13.8 ± 1.5	10.7 ± 1.3	14.6 ± 1.9
Total N (g/kg)	0.8 ± 0.2	1.2 ± 0.3	0.9 ± 0.2	0.6 ± 0.1	1.0 ± 0.2
Available P (mg/kg)	15.3 ± 3.5	22.7 ± 4.8	18.5 ± 3.9	12.1 ± 2.6	20.4 ± 4.2
Available K (mg/kg)	142 ± 25	185 ± 31	158 ± 27	118 ± 20	172 ± 29
Clay content (%)	28.5 ± 3.7	32.1 ± 4.2	30.3 ± 3.9	25.8 ± 3.3	± 4.0

3.3 Nano-Biochar Production and Characterization

Nano-biochar was made using rice husk, a locally abundant agricultural waste in the Chas region. The production process involved the following steps:

(i) Rice husk was washed, dried, and crushed to a particle size of < 2 mm.

(ii) Slow pyrolysis was performed at 500 °C for 2 hours under nitrogen atmosphere.

(iii) The resulting biochar was ground and sieved to obtain particles < 00 μm.

(iv) Nano-sized biochar was produced use a planetary ball mill (300 rpm, 4 hours).

(v) The nano-biochar was described in terms of its physicochemical characteristics.

The key characteristics of the produced nano-biochar are summarized as shown in Table 4.

Table 4. Physicochemical properties of rice husk-derived nano-biochar

Property	Value
Particle size (nm)	50-100
Specific surface area (m^2/g)	758 ± 25
Pore volume (cm^3/g)	0.85 ± 0.07
pH	8.3 ± 0.2
CEC (cmol/kg)	32.5 ± 2.8
Carbon content (%)	72.3 ± 1.5
H/C ratio	0.38 ± 0.03
O/C ratio	0.21 ± 0.02
Ash content (%)	± 0.9

3.4 Experimental Design

A random whole block design was employed to assess the consequences of nano-biochar application on soil remediation. At each study site, 5×5 m plots were established with the following treatments:

(i) Control (no amendment)

(ii) Low nano-biochar dose (5 t/ha)

(iii) Medium nano-biochar dose (10 t/ha)

(iv) High nano-biochar dose (20 t/ha)

(v) Conventional biochar (10 t/ha)

Every intervention was carried out three times, resulting in a total of 75 experimental plots across the five study sites. Nano-biochar and conventional biochar were incorporated into the top 20 cm of soil using a rotavator. The plots were irrigated to field capacity and given two weeks to reach equilibrium before the start of the experiment.

3.5 Soil Sampling and Analysis

Samples of soil were taken from each plot at 0, 30, 60, 90, and 180 days after nano-biochar application. Samples were analyzed for the following parameters:

- Heavy metal concentrations (Pb, Cd, Cr, As, Hg)
- PAH concentrations
- pH, EC, and CEC
- Organic matter content
- Microbial biomass carbon (chloroform fumigation-extraction method)
- Dehydrogenase activity (TTC method)

3.6 ANFIS Model Development

The ANFIS framework was designed to predict the optimal nano-biochar dosage based on soil characteristics and contaminant levels. The model structure consisted of the following components:

(i) Input Variables:

- Soil pH
- Organic matter content
- Clay content
- CEC
- Initial heavy metal concentrations (Pb, Cd, Cr, As, Hg)
- Initial PAH concentrations

(ii) Output Variable:

- Optimal nano-biochar dosage (t/ha)

(iii) Membership Functions:

- For every input variable, three Gaussian functions of membership were assigned.

(iv) Fuzzy Rules:

- Generated using a subtractive clustering algorithm

(v) Training Algorithm:

- Hybrid learning methodology that blends backpropagation with least squares estimation.

The ANFIS paradigm was put into practice by MATLAB R2023a Fuzzy Logic Toolbox. Training (70%), validation (15%), and testing (15%) subsets of the dataset were randomly selected. Efficiency of the model was determined using the following metrics:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

3.7 Model Validation and Comparison

The performance of ANFIS, comparisons of the models were done using the following methods:

(i) Multiple Linear Regression (MLR)

(ii) Artificial Neural Network (ANN)

(iii) Support Vector Regression (SVR)

Additionally, an experiment for field testing was carried out, at a separate contaminated site in Chas to assess the real-world performance of the ANFIS-optimized nano-biochar application.

4. Results and Discussion

4.1 Soil Contamination Assessment

The initial soil analysis revealed varying levels of contamination across the five study sites in Chas. The mean concentrations of key contaminants at each site before nano-biochar application is shown in Table 5.

Table 5. Mean concentrations (± SD) of key contaminants across study sites

Contaminant	Industrial Zone (IZ)	Agricultural Land (AL)	Urban Residential (UR)	Peri-urban Open Space (PO)	Remediated Control (RC)
Pb (mg/kg)	245.3 ± 32.7	78.5 ± 12.4	112.7 ± 18.9	52.3 ± 8.6	65.8 ± 10.2
Cd (mg/kg)	3.8 ± 0.6	1.2 ± 0.3	1.7 ± 0.4	0.8 ± 0.2	1.0 ± 0.2
Cr (mg/kg)	178.5 ± 25.3	62.3 ± 9.8	85.4 ± 13.7	41.2 ± 6.5	53.7 ± 8.4
As (mg/kg)	22.7 ± 3.5	8.9 ± 1.6	12.3 ± 2.1	5.8 ± 1.0	7.5 ± 1.3
Hg (mg/kg)	1.5 ± 0.3	0.4 ± 0.1	0.7 ± 0.2	0.3 ± 0.1	0.5 ± 0.1
Total PAHs (mg/kg)	12.8 ± 2.1	3.5 ± 0.7	5.9 ± 1.1	2.1 ± 0.4	2.8 ± 0.5

The finding shows that the Industrial Zone (IZ) showed the greatest amount of contamination for all analyzed pollutants, then the Urban Residential (UR) area. The Agricultural Land (AL) showed moderate contamination levels, likely due to the historical use of agrochemicals. The Peri-urban Open Space (PO) had the lowest contaminant concentrations among the non-remediated sites, while the Remediated Control (RC) site showed reduced contamination levels compared to the other urban and agricultural areas.

4.2 Effects of Nano-Biochar Application on Soil Properties

The application of nano-biochar resulted in significant changes in soil properties across all study sites.

Key observations from the nano-biochar application include:

(i) *Soil pH*: Nano-biochar application led to a gradual increase in soil pH across all sites, with the effect being more pronounced in the initially acidic Industrial Zone soils. The high-dose treatment (20 t/ha) resulted in a mean pH increase of 0.8 units after 180 days.

(ii) *Cation Exchange Capacity* (CEC): A significant enhancement in soil CEC was observed following nano-biochar application. The medium (10 t/ha) and high (20 t/ha) dosages resulted in CEC increases of 25% and 38%, respectively, compared to the control plots after 180 days.

(iii) *Organic Matter Content*: Nano-biochar application contributed to a substantial increase organic matter in the soil content. The high-dose treatment resulting in a 45% increase in organic matter concentration in contrast to the control after 180 days.

(iv) *Soil Structure*: Improved soil aggregation and the ability to store water were noted in nano-biochar-amended plots, particularly at the medium and high dosages.

4.3 Contaminant Immobilization and Degradation

The application of nano-biochar demonstrated significant effects on the immobilization of heavy metals and the degradation of organic pollutants.

The mean reduction percentages in bioavailable heavy metal fractions and total PAH concentrations after 180 days of nano-biochar application across all study sites are summarized as shown in Table 6.

Table 6. Mean reduction percentages (± SD) in bioavailable heavy metals and total PAHs after 180 days

Contaminant	Low dose (5 t/ha)	Medium dose (10 t/ha)	High dose (20 t/ha)	Conventional biochar (10 t/ha)
Pb	35.7 ± 4.8%	52.3 ± 6.2%	68.9 ± 7.5%	41.5 ± 5.3%
Cd	42.3 ± 5.6%	61.8 ± 7.3%	79.5 ± 8.7%	48.2 ± 6.1%
Cr	31.2 ± 4.2%	47.5 ± 5.9%	63.1 ± 7.1%	37.8 ± 4.8%
As	38.9 ± 5.1%	56.4 ± 6.7%	72.7 ± 8.3%	44.6 ± 5.7%
Hg	45.6 ± 5.9%	65.2 ± 7.8%	83.1 ± 9.2%	51.3 ± 6.5%
Total PAHs	48.3 ± 6.2%	67.9 ± 8.1%	85.4 ± 9.7%	54.7 ± 7.0%

Key findings from the contaminant immobilization and degradation analysis include:

(i) *Heavy Metal Immobilization*: Nano-biochar application significantly reduced the bioavailable fractions of all analyzed heavy metals. The high-dose treatment (20 t/ha) was most effective, with reduction percentages ranging from 63.1% for Cr to 83.1% for Hg after 180 days.

(ii) *PAH Degradation*: A substantial reduction in PAH concentrations overall were noted across all nano-biochar treatments. The high-dose application resulted in an 85.4% reduction in total PAHs after 180 days, compared to 54.7% for conventional biochar.

(iii) *Dose-Dependent Effects*: The effectiveness of contaminant immobilization and degradation showed a clear dose-dependent relationship, with higher nano-biochar dosages leading to greater reductions in bioavailable heavy metals and total PAHs.

(iv) *Site-Specific Variations*: The effectiveness of nano-biochar treatment varied across study sites, with the Industrial Zone and Urban Residential areas showing the most significant improvements due to their initially higher contamination levels.

(v) *Comparison with Conventional Biochar*: Nano-biochar consistently outperformed conventional biochar in terms of contaminant immobilization and degradation, with the medium-dose nano-biochar treatment (10 t/ha) showing greater effectiveness than the equivalent dosage of conventional biochar.

4.4 ANFIS Model Performance

The ANFIS framework was designed to predict the optimal nano-biochar dosage based on soil properties and initial contaminant levels. The performance metrics of the ANFIS model in comparison with other predictive methods are shown in Table 7.

Table 7. Performance comparison of ANFIS and other predictive models

Model	RMSE (t/ha)	MAE (t/ha)	R^2
ANFIS	1.23	0.95	0.942
Multiple Linear Regression (MLR)	3.57	2.89	0.768
Artificial Neural Network (ANN)	1.89	1.52	0.897
Support Vector Regression (SVR)	1.65	1.37	0.915

The ANFIS model demonstrated superior performance in predicting optimal nano-biochar dosages compared to other methods, with the lowest RMSE (1.23 t/ha) and MAE (0.95 t/ha), and the highest R^2 value (0.942). This indicates the ANFIS model can accurately capture the complex, nonlinear connections between soil properties, contaminant levels, and optimal nano-biochar dosages.

The strong correlation between predicted and observed values further confirms the robustness of the ANFIS model in optimizing nano-biochar application for soil remediation in Chas.

4.5 Sensitivity Analysis

To find the most crucial input variables found in the ANFIS model, a sensitivity study was carried out. Considering the sensitivity evaluation, initial heavy metal concentrations (particularly Pb and Cd) and the amount of organic matter in the soil were the most influential factors in determining optimal nano-biochar dosages. Practitioners can benefit from this knowledge in prioritizing soil testing parameters when designing remediation strategies.

4.6 Field Validation of ANFIS-Optimized Nano-Biochar Application

To assess the real-world performance of the ANFIS-optimized nano-biochar application, an experiment for field validation was carried out at a separate contaminated site in Chas. Three sections comprised the locations:

(i) Control (no amendment).

(ii) Conventional method (fixed 10 t/ha nano-biochar application).

(iii) ANFIS-optimized nano-biochar application.

Compare the contaminant reduction percentages and soil quality improvements after 180 days for the three treatments are shown in Table 8.

The field validation results demonstrate that the ANFIS-optimized nano-biochar application outperformed both the control and conventional method treatments. Key observations include:

(i) *Enhanced Contaminant Reduction*: The ANFIS-optimized treatment achieved 16.4% and 18.3% greater reductions in Pb and Cd, respectively, compared to the conventional method.

(ii) *Improved PAH Degradation*: Total PAH reduction was 18.1% higher in the ANFIS-optimized treatment compared to the conventional method.

(iii) *Soil Quality Enhancements*: The ANFIS-optimized approach resulted in more significant improvements in soil pH, CEC, and organic matter content compared to the conventional method.

Table 8. Comparison of contaminant reduction and soil quality improvements in field validation experiment

Parameter	Control	Conventional method	ANFIS-optimized
Pb reduction (%)	5.3 ± 1.2	47.8 ± 5.9	64.2 ± 7.1
Cd reduction (%)	4.7 ± 0.9	55.3 ± 6.5	73.6 ± 8.3
Total PAH reduction (%)	8.2 ± 1.5	61.7 ± 7.2	79.8 ± 9.0
pH increase (units)	0.1 ± 0.05	0.6 ± 0.1	0.8 ± 0.1
CEC increase (%)	2.5 ± 0.7	21.3 ± 3.2	32.7 ± 4.1
Organic matter increase (%)	3.1 ± 0.8	28.5 ± 3.9	39.6 ± 4.8

(iv) *Resource Efficiency*: The ANFIS-optimized treatment achieved superior results while using an average of 12% less nano-biochar compared to the fixed-rate conventional method, indicating improved resource efficiency.

These field validation results underscore the practical benefits of using the ANFIS model to optimize nano-biochar application in soil remediation projects.

5. Conclusion

This work describes how an *Adaptive Neuro-Fuzzy Inference System* (ANFIS) can be used to optimize the application of nano-biochar in soil remediation initiatives in Chas, Bokaro, Jharkhand, India. The use of nano-biochar derived from the husk of rice considerably enhanced soil properties and reduced contaminant level. The developed ANFIS model demonstrated superior performance in predicting optimal nano-biochar dosages compared to conventional methods. Perform a comprehensive cost-benefit analysis of implementing ANFIS-optimized nano-biochar remediation compared to conventional methods. This study demonstrates the powerful potential of combining advanced computational techniques with innovative remediation materials to address complex soil contamination challenges. The ANFIS-optimized nano-biochar application approach developed here offers a promising tool for environmental managers and policymakers working to restore contaminated soils and protect ecosystem and human health in rapidly developing urban areas.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

References

[1] M. Ahmad, A. U. Rajapaksha, J. E. Lim, M. Zhang, N. Bolan, D. Mohan, M. Vithanage, S. S. Lee and Y. S. Ok, Biochar as a sorbent for contaminant management in soil and water: a review, *Chemosphere* **99** (2014), 19 – 33, DOI: 10.1016/j.chemosphere.2013.10.071.

[2] M. Ahmadlou, M. Karimi, S. Alizadeh, A. Shirzadi, D. Parvinnejhad, H. Shahabi and M. Panahi, Flood susceptibility assessment using integration of adaptive network-based fuzzy inference system (ANFIS) and biogeography-based optimization (BBO) and BAT algorithms (BA), *Geocarto International* **34**(11) (2018), 1252 – 1272, DOI: 10.1080/10106049.2018.1474276.

[3] B. J. Alloway, Heavy Metals in Soils: Trace Metals and Metalloids in Soils and their Bioavailability, 3rd edition, Springer, (2013), DOI: 10.1007/978-94-007-4470-7.

[4] R. Bian, S. Joseph, L. Cui, G. Pan, L. Li, X. Liu, A Zhang, H. Rutlidge, S. Wong, C. Chia, C. Marjo, B. Gong, P. Munroe and S. Donne, A three-year experiment confirms continuous immobilization of cadmium and lead in contaminated paddy field with biochar amendment, *Journal of Hazardous Materials* **272** (2014), 121 – 128, DOI: 10.1016/j.jhazmat.2014.03.017.

[5] J.-S. R. Jang, ANFIS: adaptive-network-based fuzzy inference system, *IEEE Transactions on Systems, Man and Cybernetics* **23**(3) (1993), 665 – 685, DOI: 10.1109/21.256541.

[6] J.-S. R. Jang, C.-T. Sun and E. Mizutani, *Neuro-Fuzzy and Soft Computing: a Computational Approach to Learning and Machine Intelligence*, Prentice Hall, Upper Saddle River, NJ, xxvi + 614 pages (1997).

[7] O. Kisi and M. Ay, Comparison of ANN and ANFIS techniques in modeling dissolved oxygen, in: *Proceedings of the 16th International Water Technology Conference* (IWTC16), Istanbul, Turkey (2014).

[8] S. Kuppusamy, T. Palanisami, M. Megharaj, K. Venkateswarlu and R. Naidu, In-situ remediation approaches for the management of contaminated sites: a comprehensive overview, in: *Reviews of Environmental Contamination and Toxicology*, P. de Voogt (editor), Vol. **236**, Springer, Cham., DOI: 10.1007/978-3-319-20013-2_1.

[9] J. Lehmann, M. C. Rillig, J. Thies, C. A. Masiello, W. C. Hockaday and D. Crowley, Biochar effects on soil biota — a review, *Soil Biology and Biochemistry* **43**(9) (2011), 1812 – 1836, DOI: 10.1016/j.soilbio.2011.04.022.

[10] J. J. Manya, Pyrolysis for biochar purposes: a review to establish current knowledge gaps and research needs, *Environmental Science & Technology* **46**(15) (2012), 7939 – 7954, DOI: 10.1021/es301029g.

[11] A. Mellit and S. A. Kalogirou, ANFIS-based modelling for photovoltaic power supply system: A case study, *Renewable Energy* **36**(1) (2011), 250 – 258, DOI: 10.1016/j.renene.2010.06.028.

[12] P. C. Nayak, K. P. Sudheer, D. M. Rangan and K. S. Ramasastri, A neuro-fuzzy computing technique for modeling hydrological time series, *Journal of Hydrology* **291**(1-2) (2004), 52 – 66, DOI: 10.1016/j.jhydrol.2003.12.010.

[13] L. Ouyang, F. Wang, J. Tang, L. Yu and R. Zhang, Effects of biochar amendment on soil aggregates and hydraulic properties, *Journal of Soil Science and Plant Nutrition* **13**(4) (2013), 991 – 1002, DOI: 10.4067/S0718-95162013005000078.

[14] L. Qian, B. Chen and D. Hu, Effective alleviation of aluminum phytotoxicity by manure-derived biochar, *Environmental Science & Technology* **47**(6) (2013), 2737 – 2745, DOI: 10.1021/es3047872.

[15] R. Setia, P. Gottschalk, P. Smith, P. Marschner, J. Baldock, D. Setia and J. Smith, Soil salinity decreases global soil organic carbon stocks, *Science of The Total Environment* **465** (2013), 267 – 272, DOI: 10.1016/j.scitotenv.2012.08.028.

[16] R. M. S. Sharma and N. S. Raju, Correlation of heavy metal contamination with soil properties of industrial areas of Mysore, Karnataka, India by cluster analysis, *International Research Journal of Environment Sciences* **2**(10) (2013), 22 – 27.

[17] X. Tan, Y. Liu, G. Zeng, X. Wang, X. Hu, Y. Gu and Z. Yang, Application of biochar for the removal of pollutants from aqueous solutions, *Chemosphere* **125** (2015), 70 – 85, DOI: 10.1016/j.chemosphere.2014.12.058.

[18] O. Taylan, Modelling and analysis of ozone concentration by artificial intelligent techniques for estimating air quality, *Atmospheric Environment* **150** (2017), 356 – 365, DOI: 10.1016/j.atmosenv.2016.11.030.

[19] Y. Yao, B. Gao, M. Zhang, M. Inyang and A. R. Zimmerman, Effect of biochar amendment on sorption and leaching of nitrate, ammonium, and phosphate in a sandy soil, *Chemosphere* **89**(11) (2012), 1467 – 1471, DOI: 10.1016/j.chemosphere.2012.06.002.

[20] M. Zhang and B. Gao, Removal of arsenic, methylene blue, and phosphate by biochar/AlOOH nanocomposite, *Chemical Engineering Journal* **226** (2013), 286 – 292, DOI: 10.1016/j.cej.2013.04.089.

[21] X. Zhang, H. Wang, L. He, K. Lu, A. Sarmah, J. Li, N. S. Bolan, J. Pei and H. Huang, Using biochar for remediation of soils contaminated with heavy metals and organic pollutants, *Environmental Science and Pollution Research* **20** (2013), 8472 – 8483, DOI: 10.1007/s11356-013-1659-0.