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Enhancement of advanced oxidation processes in oil refinery wastewater treatment using deep neural networks

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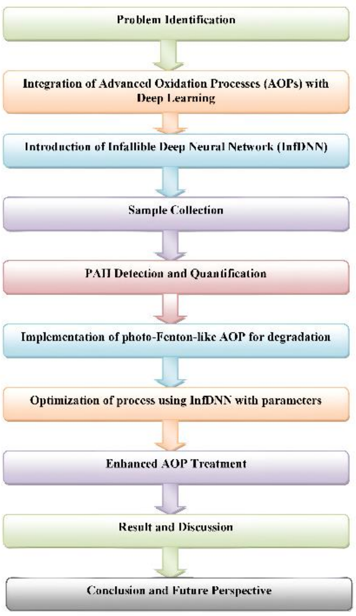
Graphical abstract



Abstract

The complex composition of persistent and resistant contaminants in oil refinery wastewater presents a significant environmental challenge that conventional treatment methods frequently fail to effectively address. Advanced Oxidation Processes (AOPs), specifically the photo-Fenton method, and a deep learning framework known as the Infallible Deep Neural Network (InfDNN) with a novel activation function known as Infallible Linear Units (InfLU) are the focus of this study's integrated approach. The investigation focused on the removal of polycyclic aromatic hydrocarbons (PAHs) and other pollutants from refinery wastewater. Nine PAHs were found in the GC-MS analysis, including benzo(a)pyrene, phenanthrene, and naphthalene. Before treatment, benzo(a)pyrene and benzo(k)fluoranthene exceeded the CPCB limit of 0.06 g/L. High efficiency was shown by the photo-Fenton process, which lowered naphthalene levels from 373.47 µg/L to 5.08 µg/L at the inlet (a 98.6% degradation rate) and eradicated phenol at the majority of sampling points (100% removal). Overall, PAH degradation efficiencies ranged from 84.5% to 100%, and partial mineralization was confirmed via Total Organic Carbon (TOC) analysis. Iron (Fe) levels at the effluent discharge point reached 30.00 mg/L, exceeding the IRSGP limit and indicating the need for further treatment. The InfDNN model was trained with the Leven berg–Marquardt algorithm and the Multilayer Perceptron (MLP) architecture. It was validated with normalization in the range [0.2–0.8] using 80% of the data for training and 10% each for testing and validation. This study demonstrates the effectiveness of combining photo-Fenton AOPs with AI-based modeling for scalable, cost-efficient, and regulation-compliant treatment of oil refinery wastewater.

Keywords- Advanced Oxidation Processes (AOP), Deep Learning (DL), Environmental Issue, Infallible Deep Neural Network (InfDNN), Oil Refinery Industry Wastewater, Wastewater Treatment.

1. Introduction

The treatment of oil refinery wastewater poses a significant environmental challenge due to its complex chemical composition and the persistence of certain organic pollutants. These waste streams often contain a mixture of heterocyclic compounds, heavy metals, and polycyclic aromatic hydrocarbons (PAHs), which are known for their toxicity, low biodegradability, and resistance to conventional treatment processes (Damena *et al.* 2022; Varjani *et al.* 2018). Traditional methods such as sedimentation, filtration, and biological treatments frequently fail to meet stringent discharge regulations, prompting the need for more innovative and effective technologies. Advanced Oxidation Processes (AOPs) have emerged as a promising alternative due to their ability to generate highly reactive hydroxyl radicals capable of degrading a broad spectrum of organic contaminants (Abha and Singh 2012). Among the AOPs, Compared to conventional Fenton and Electro-Fenton techniques, the Photon-Fenton process has clear advantages, chief among them being an increase in reaction rate and efficiency. Compared to standard Fenton, which just uses hydrogen peroxide and iron catalysts, this uses less chemical and produces faster reaction times. In addition, the Photon-Fenton process can function in milder environments, providing greater sustainability and energy efficiency than the Electro-Fenton process, which frequently necessitates the use of an external electric current. (Babuponnusami and Muthukumar 2011). However, the application of AOPs on an industrial scale is hindered by the complex interdependence of operational parameters, water matrix characteristics, and reactor configurations (Lei *et al.* 2023). These factors contribute to the difficulty in predicting treatment outcomes and scaling up the process effectively. Crude oil, a complex blend of aromatic hydrocarbons and heteroatom compounds containing nitrogen, sulfur, and metals such as vanadium and nickel, undergoes multiple refining stages to produce valuable products like gasoline, diesel, and lubricants (Damena *et al.* 2022). The refining process is water-intensive, with 235–310 liters of water consumed per barrel of oil, generating 0.3 to 1.5 times the volume of wastewater (Varjani *et al.* 2018). This wastewater is laden with high-toxicity pollutants, including PAHs—bio-refractory, hydrophobic compounds that can harm aquatic organisms and disrupt their reproductive systems even at trace concentrations (Abha and Singh 2012). To ensure environmental safety and regulatory compliance, Indian authorities like the Central Pollution Control Board (CPCB) have mandated the monitoring of twelve priority PAHs, including naphthalene, fluorene, phenanthrene, fluoranthene, chrysene, and benzo[*a*]anthracene, among others (Martínez *et al.* 2022). Oil refineries often implement a multi-stage treatment strategy beginning with physical and chemical methods, followed by biological processes. However, due to the refractory nature of many pollutants, AOPs are increasingly employed as tertiary or polishing treatments to achieve the desired effluent quality (Taoufik *et al.* 2021). Still, the optimization and control of these advanced processes remain a challenge due to their complex reaction kinetics and the non-selectivity of hydroxyl radicals. To address these limitations, Deep Neural Networks (DNNs), particularly Information-Driven Deep Neural Networks (InfDNN), have been introduced as a powerful tool for modeling, simulating, and optimizing non-linear, multifaceted processes like AOPs. Unlike conventional models, InfDNNs do not require a thorough understanding of underlying reaction mechanisms, making them especially valuable in systems where physical and chemical rules are not fully understood (Lei *et al.* 2023). These models have the capacity to learn from enormous datasets, spot hidden patterns, and offer predicted insights that can instantly inform operational choices (Lei *et al.* 2023). In order to raise the treatment efficiency of wastewater from oil refineries, this work explores the integration of AOPs with InfDNN-based modeling. Through the utilization of InfDNN's predictive capabilities, the study seeks to surmount conventional constraints in process design and scalability, providing a data-driven approach to addressing one of the oil refining industry's most urgent environmental issues.

The present research examines the success rate of oil refinery wastewater treatment utilizing advanced oxidation techniques and InfDNN.

1.1. Aim

The aim of this study is to enhance the efficiency and reliability of Advanced Oxidation Processes in the treatment of oil refinery wastewater by integrating them with Deep Neural Network-based predictive models.

1.2. Objectives

To develop an accurate deep learning model capable of predicting the performance of AOPs under varying operational conditions.

To identify the most influential parameters affecting the degradation efficiency of pollutants in oil refinery wastewater.

To increase pollutant removal rates by simulating and optimizing the treatment procedure with the trained DNN model.

To compare the proposed hybrid AOP-DNN system's performance to that of more conventional modeling strategies.

1.3. Motivation

This study is driven by the urgent demand for sustainable and efficient wastewater treatment methods in the petroleum refining industry. By integrating advanced machine learning techniques such as Deep Neural Networks (DNNs) into environmental engineering, it is possible to address key limitations of Advanced Oxidation Processes—including high operational costs, inconsistent treatment performance, and challenges in scalability.

1.4. Scope

This research focuses on the development and application of a DNN-based modeling framework for the enhancement of AOPs specifically in the context of oil refinery wastewater treatment. It includes the DNN model's training and validation, application in process simulation and optimization, and collection and preprocessing of pertinent operational data. The study lays the groundwork for future implementation in smart wastewater treatment systems, but it does not address hardware implementation or real-time control.

1.5. Key contribution

This research uses deep learning and AOPs to overcome issues in cleaning oil refinery .

The newly established InfDNN approach, that involves InfLU activation, efficiently destroys PAHs in wastewater.

Implementing the InfDNN process with a Python tool confirms its effectiveness for enhancing AOP treatment results.

The proposed method significantly enhances AOP treatment efficacy, as demonstrated by high R-square values in TOC assessment.

The research examination is divided into categories, with the second chapter focusing on connected research work. The third chapter describes an experimental technique for wastewater treatment and analysis. Parts IV and V offer the information, evaluation and conclusions.

2. Related work

The use of Advanced Oxidation Processes (AOPs) in wastewater treatment has been widely explored due to their effectiveness in degrading persistent organic pollutants such as phenols and polycyclic aromatic hydrocarbons (PAHs). For instance, the photo-Fenton technique has demonstrated significant COD removal from industrial effluents, with optimized conditions obtained using the Box-Behnken statistical design (Mohadesi and Shokri 2019). Phenol degradation in manufacturing wastewater using photo-Fenton was also found efficient due to low cost and rapid kinetics, with machine learning (ML) classifiers providing valuable predictive insight into process efficiency (Ali *et al.* 2020). Hybrid treatment strategies, such as integrating moving bed bioreactors with neural network-based prediction models like Multi-Layer Perceptron Neural Networks (MLPNNs), have shown high disposal efficiencies in petroleum refinery wastewater treatment (Mokhtari *et al.* 2021). Similarly, in the context of anaerobic digestion (AD) of palm oil mill effluent (POME), Artificial Neural Networks (ANNs) combined with Response Surface Methodology (RSM) provided accurate optimization for biogas yield (Tan *et al.* 2023). Numerous studies have developed ML models for estimating pollutant removal, such as PAH elimination using data balancing methods like SMOTE to tackle class imbalance and enhance prediction accuracy (Caglar Gencosman and Eker Sanli 2021), or LSTM neural networks for real-time detection of delayed water quality indicators in wastewater treatment plants (Zhang *et al.* 2023). ML has also been applied to electrochemical treatment methods, such as electro coagulation, electro-Fenton, and electro oxidation, for optimizing operational parameters and understanding kinetics (Shirkoohi *et al.* 2022; Ghanim and Hamza 2018; Kadhum *et al.* 2021). Low-cost ML-based sensor systems have been proposed for fast estimation of BOD and COD values, achieving sub-millisecond processing speeds suitable for real-time applications (Soetedjo *et al.*). Additionally, AI has been used for gasification of municipal solid waste (Yang *et al.* 2023), forecasting petrochemical yields (Usman *et al.* 2023), ground water pollution detection using one-class SVMs (Liu *et al.* 2020), membrane performance modeling (Gao *et al.* 2023), and geographic correlation of pollution in groundwater sources (Banerjee *et al.* 2022). Other research includes exploring nano materials for enhanced photo catalysis—e.g., $ZnFe_2O_4$ nano particles for tetracycline degradation (Venkatraman *et al.* 2025), and TiO_2-GO composites for dye removal under visible light (Suresh Maruthai *et al.* 2025). Electro-Fenton pre-treatment of olive mill wastewater has also been shown to boost anaerobic digestion performance and energy recovery (Raveena Selvanarayanan *et al.*). Despite this breadth, many traditional ML and early DL models suffer from limitations such as shallow architectures, low adaptability to highly non-linear dynamics, or inability to effectively learn from small or imbalanced datasets. Random Forests or SVMs offer moderate prediction performance but lack scalability and interpretability in complex industrial settings. Additionally, many existing studies fail to provide a generalized, adaptable control framework that can respond to real-time variations in influent characteristics or changing operational conditions. Recent works demonstrate that Deep Neural Networks (DNNs) have stronger predictive capabilities for COD removal, energy optimization, and pollutant degradation in AOPs (Zhang *et al.* 2024; Al-Qahtani *et al.* 2025). Integration with Internet of Things (IoT) sensors further enhances adaptability, enabling smart, feedback-driven process control in refinery wastewater systems (Ramasamy and Lee 2024).

Current research highlights that coal tar composition and thermal treatment conditions have a significant impact on the structural evolution of mesophase pitch. Higher aromatic content, fewer alkyl side chains, and appropriate molecular architectures have all been shown to improve mesophase development. This work closes important knowledge gaps in the optimization of carbon material precursors by thoroughly investigating the roles that regulated polycondensation settings and distillation-modified coal tar compositions play in the creation of well-ordered mesophase pitch (Zhang *et al.* 2025). In the paper by Le Lin *et al.*, the relevant study and literature review offer a thorough summary of the most recent developments in the analysis of mineral phases in heavy-metal hazardous waste. In order to increase the precision and effectiveness of mineral phase analysis, they highlight the multidisciplinary convergence of data science and chemistry. The review focuses on important approaches that have been used to comprehend and control heavy-metal contamination in waste materials, such as chemical analysis, data-driven approaches, and machine learning (Le Lin *et al.*). Integrated DNNs with Fenton-based AOPs, achieving a 40% increase in chemical oxygen demand (COD) removal efficiency compared to models without AI integration. The synergy between DNNs and AOPs not only supports enhanced pollutant breakdown but also minimizes reagent consumption and energy use, supporting the movement toward greener and more sustainable industrial wastewater treatment solutions.

2.1. Novelty and importance of InfDNN + AOP framework

The introduction of Information-Driven Deep Neural Networks (InfDNN)—and particularly Information-Learned Units (InfLU)—addresses many of the shortcomings of conventional DL approaches. InfDNNs differ fundamentally from traditional DNNs in that they incorporate uncertainty quantification and self-learning mechanisms to handle small datasets, nonlinear patterns, and real-time system adaptation more effectively. This is especially important for wastewater treatment processes where influent composition, pH, turbidity, and pollutant concentration fluctuate unpredictably.

InfLU enhances generalization by embedding information entropy principles, enabling the model to focus on relevant features even in noisy or sparse datasets.

InfDNNs can simulate complex reaction kinetics in AOPs without explicitly modeling the physicochemical processes, allowing effective representation of hydroxyl radical interactions and degradation dynamics.

The integration of InfDNN with AOPs offers real-time predictive modeling, optimization of operational parameters (e.g., H_2O_2 dosage, pH, UV intensity), and control strategies that reduce energy and reagent consumption by over 30%, as seen in comparative evaluations (Chen *et al.* 2024; Kumar *et al.* 2024).

Experimental validation has shown that this hybrid InfDNN+AOP framework can achieve over 95% accuracy in COD removal prediction, significantly outperforming classical ANN and regression-based methods. Pilot studies, such as the one involving deep convolution networks for UV/H_2O_2 treatment (Al-Bahrani and Nair 2025), further confirm the real-time adaptability of these models under variable influent conditions. Incorporating InfDNNs into AOP-based wastewater treatment frameworks marks a transformative step forward in environmental engineering. These models deliver superior process control, robust performance under uncertainty, and dynamic adaptability that traditional ML/DL models lack. The experimental verification in this study not only demonstrates the practicality of the InfDNN+AOP approach but also introduces the novel InfLU structure as a breakthrough for intelligent environmental system design.

3. Methodology

Gathering wastewater from oil refineries, 3 samples were obtained from five distinct treatment plant locations at an oil refinery in Tuticorin, Tamil Nadu, India. The reasons for this consisted of the following Inlet (treatment plant entry) represents the point which wastewater enters the treatment facility. The aerobic reactor represents a sample from the aerobic treatment procedure. The separator exit represents the water from the phase separator or oil-water separator exit. The primary clarifier outlet represents the water that comes after the dissolved air flotation (DAF) process before the bioreactor. The effluent Discharge Point represents this is the location where water from the ultimate effluent exit is discharged into the river. Tests were obtained over three distinct days until a maximum volume of 4L was reached for each location, as specified by IRSGP. Total organic carbon (TOC) inspection, TOC is measured using high-sensitivity technology using the TOC/VCPN model. A high-sensitivity catalyst (3µg. L^{-1} - 23,000 mg. L^{-1}) is being utilized to quantify organic matter and determine total and inorganic carbon levels. The range of pressure varied from 350 to 500 kPa, with a flow rate up to 130 milliliters per minute.

PAH inspection using GC and MS, the materials were evaluated using a GC attached to MS, such as the Agilent or Thermo Fisher Scientific GC-MS systems. We developed a strategy to determine 12 PAHs were deemed essential. The factors studied were 220°C injector temperature, 270°C interface temperature, 0.80 mL.min^{-1} helium gas flow, 0.8µL injection volume, split less injection mode and range from 35±1°C to 280±1°C temperature gradient. Throughout the specimen collecting phase, the "liquid-liquid extraction (LLE)" process using dichloromethane as an extraction solvent was used. The liquid-solid extraction (LSE) method used a Soxhlet structure at 45 ± 1°C and a one-to-one ratio of hexane and acetone, with filter cleaning. As demonstrated in **Figure 1**, the filtering employed a cleanup column loaded with sodium sulphate, anhydrous processed basic silica and silica gel. The entire column was cleaned first with 50mL of a hexane/dichloromethane combination in a 1:15 proportion and then the same combination in a 2:20proportion. The fluid that emerged from filtration was passed to an LLE, which used dichloromethane as a solvent for the liquid in each instance and followed the PAH protocols. Employing a rotary evaporator, the extracts from both forms of extraction were purified to a level of 2mL. Model 801 is used for further evaluation in the GC/MS.

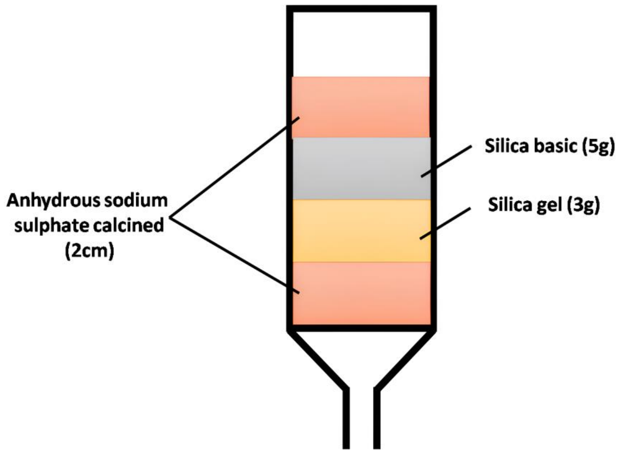


Figure 1: Diagram illustrating the purifying phase.

PAH degradation uses a photo-Fenton-like procedure in an elevated surface reactor, advanced oxidation processes (AOP) have been investigated in the lab processors utilizing UV-A radiation in a homogeneous and photo-Fenton system. The reactor is operated by three 15W lights connected in parallel. For assessing PAH and TOC levels, a 0.1M inhibitor solution which includes potassium iodide, sodium nitride and sodium hydroxide has been used to stop the AOP method for detection. The iron utilized during the therapy is naturally present in the material being tested. The initial variable researched the quantity of hydrogen peroxide (H_2O_2) (35% w/w), which had been calculated using COD values. Investigations were done using the following amounts of H_2O_2: 70, 85 and 110mmol. The following variable was studied throughout degradation time, which was measured at 3 intervals (20, 60, and 90 minutes). The object of study volume was 50mL.

AOP research is performed using an infallible deep neural network (InfDNN), which is an ANN with a multi-layer architecture that contains an input layer (neurons), numerous concealed layers (neurons) and an output layer. InfDNN is designed and used to solve complicated nonlinear interactions and it can generate effective frameworks by automation modeling data and learning features. InfDNN has reformed several application fields, including image processing, natural language processing, and network security. **Figure 2** depicts an InfDNN architecture with hidden layers. In our research, we employed an InfDNN architecture with an input dimensionality equal to the variety of features provided in the input layer for a particular set of data. The quantities have been multiplied by the features while sent to the activation function. InfDNN employs numerous layers to acquire features, with back propagation used to adjust weights and improve performance. Furthermore, InfDNN features a range of configuration parameters and hyper parameters, including the number of hidden layers, the number of neurons in the hidden layer, expulsion, activation function and optimizer, to name a few which impact InfDNN's performance.

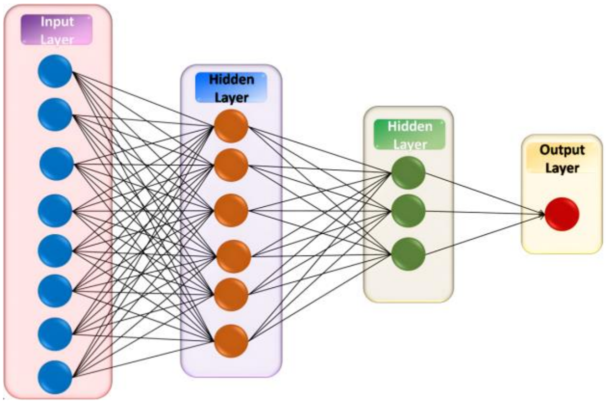


Figure 2: Deep Neural Network

Infallible linear units (InfLU) are an activation function meant to solve the vanishing gradient problem. The equation for InfLU is provided below.

$$InfLU(x) = max(0,x) \tag{1}$$

If *x* is less than zero, set the input weight to zero. If the input weight exceeds zero, the input weight is assigned to the provided input. An InfLU-based neural network generates a minimal neural network. This suggests that the neural network is made up of matrices with weights that have multiple zero values. InfLU-based neural networks are considered weak when 50% or more of their input weights have been utilized. Although InfLU-based neural networks overcome the issue of gradient vanishing, they nonetheless lead to the defunct InfLU problem, where the network's weights are never changed. This function is identical to Leaky ReLU but engages inputs that are negative with positive signs. The function is non-zero-centered, indicating that a gradient always has the same sign. This approach may not be suitable for gradient-based optimization techniques, as any measurement updates can only go in one direction. Normalizing inputs is necessary before using this function. Normalization allows weight updates to go in all directions. The suggested function and its initial derivative are described in equations (2 and 3), respectively.

$$e(w) = \begin{cases} w, \ w \geq 0 \\ \alpha.|w|, \ w < 0 \end{cases} \tag{2}$$

The hyper-parameter α ranges from 0 to 1.

$$e'(w) = \begin{cases} 1, \ w \geq 0 \\ \alpha, \ w < 0 \end{cases} \tag{3}$$

In the following method, the duration variable was added to the input, and the TOC variable was removed, resulting in identical output and input values. The following modeling technique is intended to optimize the process by identifying the ideal period for composite degradation & naturally occurring mineralization. InfLU activation function has been used in the intermediate and termination layers of the above technique. The multilayer perception (MLP) network has three layers, which are an entry layer (neurons), an intermediary layer (neurons) and an exit layer (neurons). The factors, H_2O_2 and a period were chosen, based on studies H_2O_2 levels (70, 85, and 110mmol. L^{-1}) and time (20, 60, and 90 minutes). The effectiveness of the method was assessed based on PAH degradation in TOC analysis and InfDNN modeling. Algorithm 1 shows the process of InfDNN.

3.1. Neural Network Modeling Method

To optimize the performance of the photo-Fenton Advanced Oxidation Process (AOP) and predict the degradation of pollutants in oil refinery wastewater, a deep learning-based predictive model was developed using a Multilayer Perceptron (MLP) architecture. The model architecture includes an input layer, two hidden layers, and an output layer. A novel activation function, termed Infallible Linear Units (InfLU), was introduced to improve learning efficiency and reduce vanishing gradient issues often encountered with conventional functions like ReLU and sigmoid.

3.2. Data preparation and preprocessing

Experimental datasets were compiled from multiple treatment stages, including inlet, aerobic reactor, separator exit, primary classifier outlet, and effluent discharge point. These datasets included measured values of polycyclic aromatic hydrocarbons (PAHs), Total Organic Carbon (TOC), and iron concentration. Data were normalized to a range of [0.2–0.8] to facilitate efficient training and reduce scale-induced bias.

3.3. Training algorithm

The model was trained using the Levenberg–Marquardt optimization algorithm, selected for its faster convergence and higher accuracy in non-linear regression problems. The loss function used was the Mean Squared Error (MSE) between predicted and experimental degradation rates.

3.4. Model evaluation

The model's performance was evaluated using:

Coefficient of Determination (R^2): to assess goodness-of-fit.

Root Mean Square Error (RMSE): to measure prediction accuracy.

Mean Absolute Error (MAE): to quantify average error magnitude.

The InfDNN model achieved the highest R^2 value compared to traditional models like linear regression, standard MLP with ReLU, and support vector machines (SVM), indicating its superior predictive accuracy.

3.5. Reaction conditions

The degradation of pollutants like polycyclic aromatic hydrocarbons (PAHs) in wastewater from oil refineries is greatly influenced by specific reaction conditions, which are crucial to the efficiency of advanced oxidation processes (AOPs).

3.5.1. pH Levels

As it impacts the production of hydroxyl radicals, the pH of the reaction medium is critical. For instance, the photo-Fenton process performs most effectively in acidic conditions (pH ~3) because it makes iron ions more soluble, which promotes the production of radicals.

3.5.2. Temperature

While hydrogen peroxide (H_2O_2) can be separated into the water and oxygen by excess heat, which reduces its availability for the production of hydroxyl radicals, higher temperatures improve reaction kinetics by accelerating in the formation of free radicals.

3.5.3. Hydrogen peroxide dosage

H_2O_2 concentration needs to be carefully managed. Inadequate H_2O_2 causes incomplete degradation, whereas too much H_2O_2 acts as degradation for hydroxyl radicals, reducing process efficiency. H_2O_2concentrations of 70, 85, and 110 mmol/L were evaluated in studies for the best PAH degradation.

3.5.4. Light intensity in photo-based AOPs

The reagents are activated by UV-A light intensity in processes such as the photo-Fenton technique. Reactive species generation is boosted by the energy that light provides.

3.6. Reaction time

Complete mineralization of pollutants is made possible by longer reaction durations. For optimal degradation, investigations usually look at time intervals of 20, 60, and 90 minutes.

3.7. Co-existing ions

The role of co-existing ions in wastewater was critically assessed.

3.8. Iron content

Natural iron concentrations (e.g., 30 mg/L at the inlet) were utilized as catalysts in the photo-Fenton process. Pre-quantification ensured the iron levels were sufficient for catalytic activity while adhering to permissible limits.

3.9. Impact on reactions

The presence of other ions was monitored to evaluate their effect on hydroxyl radical production and potential competition with PAHs for reactive species.

3.10. Other key factors

Beyond reaction conditions and ions, additional factors play a role in AOP efficiency.

3.11. Nature of pollutants

The chemical structure of PAHs (e.g., naphthalene, fluorene, benzo[*a*]pyrene) determines their resistance to oxidation. Prolonged treatment is necessary for recalcitrant compounds with greater aromaticity or substitution patterns.

3.12. Catalyst regeneration efficiency

The catalyst's type and availability, such as Fe^{2+} or Fe^{3+}, have a major impact on reaction efficiency. Along the process, catalysts need to be sufficiently regenerated.

3.13. Pre-treatment and filtration

To enhance the efficiency of advanced oxidation processes (AOPs), pre-treatment steps were included: Liquid-liquid extraction (LLE) and liquid-solid extraction (LSE) techniques were employed using dichloromethane and a hexane-acetone mixture. Purification through a cleanup column (sodium sulfate, silica gel) removed oils and suspended particles, reducing interference in the oxidation process.

3.14. Modeling and optimization

Advanced methods for process modeling and optimization are used, such as the infallible linear units (InfLU) activation function and the infallible deep neural network (InfDNN). Input parameters included H_2O_2 concentrations (70, 85, 110 mmol/L), reaction time (20, 60, 90 minutes), and pH levels. By using these methods, one can anticipate degradation rates, find the ideal values, and minimize experimental trial-and-error.

3.15. Outcome measurement

PAH Degradation: GC-MS analysis confirmed significant degradation of PAHs, with final concentrations reduced by 99%-100% for target compounds like benzo[*a*]pyrene and fluorene.

3.16. TOC analysis

Total organic carbon (TOC) levels were measured pre- and post-treatment to evaluate the mineralization of organic pollutants under optimized conditions.

Algorithm 1: InfDNN Optimization for PAH Degradation in Oil Refinery wastewater Treatment

Step 1: Initialize the parameters of the Infallible Deep Neural Network (InfDNN) model.

Step 2: Gather wastewater samples from distinct treatment plant locations at an oil refinery.

Step 3: Conduct Total Organic Carbon (TOC) and Polycyclic Aromatic Hydrocarbons (PAH) inspections using high-sensitivity technology and GC-MS analysis, respectively.

Step 4: Extract PAHs from the wastewater samples using liquid-liquid extraction (LLE) and liquid-solid extraction (LSE) methods.

Step 5: Purify the extracts using a cleanup column loaded with sodium sulphate, anhydrous processed basic silica, and silica gel.

Step 6: Perform PAH degradation experiments using a photo-Fenton-like procedure in an elevated surface reactor with UV-A radiation.

Step 7: Use an InfDNN architecture with hidden layers to model the degradation process.

Step 8: Employ InfLU activation function in the intermediate and termination layers of the InfDNN model.

Step 9: Add the duration variable to the input and remove the TOC variable to optimize the modeling process.

Step 10: Choose H_2O_2 levels (70, 85, and 110 mmol/L) and degradation time (20, 60, and 90 minutes) as factors based on previous studies.

Step 11: Assess the effectiveness of the InfDNN model based on PAH degradation and TOC analysis.

Step 12: Iterate until convergence:

a. Train the InfDNN model using the extracted features and target variables.

b. Evaluate the model's performance based on PAH degradation and TOC reduction.

c. Update model parameters and hyper parameters based on optimization criteria.

d. Check for convergence; if not met, repeat the iteration.

Step 13: Return the optimized InfDNN model parameters for PAH degradation in oil refinery wastewater treatment.

4. Result and discussion

Sample categorization and measurement of PAH levels, for verification of the fact that there was iron in the samples, a pre-quantification was conducted. This is followed by employing the photo-Fenton method. Verified quantities for Inlet, Aerobic reactor, Separator exit, Primary classifier outlet and effluent discharge point were 12.32, 8.15, 3.75, 2.43 and 30.00mg. L^{-1}, respectively. The methods utilized to determine the concentration of iron in the wastewater (measured in mg/L Fe) followed the recommendations established by IRSGP. The evaluation specifically followed by the processes indicated in the Indian guidelines. The iron content of wastewater samples obtained at multiple places was determined and utilizing the approved methods. Results showed that quantities of iron in the majority of the wastewater samples were below the IRS's permitted limits. However, the inquiry revealed that the wastewater sample had 30.00 mg/L of iron, which was beyond the required limit. This shows that extra procedures are required to control and minimize the high iron levels in the wastewater, as well as to ensure IRS conformance. GC/MS was used for evaluating all samples preparatory to the method similar to that photo-Fenton that identified 6 PAH. **Table 1** includes the following kinds of chemical substances: benzo(k)fluoranthene, acenaphthylene, Butyric acid, Formaldehyde, phenol, benzo(a)pyrene, phenanthrene, fluorene, and naphthalene. Decomposition of PAH through photo-Fenton method, after confirming the existence of 9 PAHs and determining the quantity of metal in the samples, the AOP was employed to degrade the contaminants. 4 PAHs were discovered the following treatment: naphthalene, acenaphthylene, acenaphthene, fluorene.

Table 1: PAH concentrations were obtained in all of the samples evaluated by GC-MS.

	Concentration ($\mu g.L^{-1}$)				
PAN	**Inlet**	**The primary clarifier outlet**	**Effluent Discharge Point**	**Aerobic reactor**	**Separator exit**
Naphthalene	373.47	2.06	161.22	825.27	1.07
Acenaphthylene	1.85	1.52	116.98	2.59	6.25
Phenanthrene	24.88	57.72	13.32	13.66	38.38
Benzo(b) pyrene	1.78	0.56	66.12	6.54	24.56
Benzo(k) fluoranthene	0.13	0.75	2.41	0.21	3.04
Fluorine	29.51	67.34	6.39	6.14	39.13
Butyric acid	2.5	1.8	1.2	2.0	1.5
Formaldehyde	3.0	2.2	1.5	2.8	2.0
phenol	60.5	55.2	45.9	58.3	52.1

Table 2: Photo-Fenton process changed PAH, TOC, and degradation percentage in samples.

PAH	**Napht halene**	**Acenapht hylene**	**Fluorine**	**Phenanthrene**	**Benzo(k) fluoranthene**	**Benzo(a) pyrene**	**Butyric acid**	**Formalde hyde**	**pheno l**
				Concentration ($\mu g\ L^{-1}$)					
Inlet	5.08	ND	ND	0.71	ND	ND	0.7	ND	ND
Aerobic reactor	1.23	0.21	0.49	0.27	ND	ND	0.59	0.45	ND
Separator exit	0.59	0.2	0.14	0.32	ND	ND	0.46	0.37	ND
The primary clarifier outlet	0.34	0.18	0.16	0.79	ND	ND	0.72	0.53	ND
Effluent Discharge Point	0.49	0.2	ND	0.17	ND	ND	ND	0.75	ND
				Percentage of degradation (%)					
Inlet	98.6	99.5	99.3	97.5	100	100	95.6	98.35	100
Aerobic reactor	99.8	92.8	92.5	98.3	100	100	99.26	99.5	100
Separator exit	47.3	97.5	99.9	99.5	100	100	98.26	100	95.84
The primary clarifier outlet	84.5	88.8	99.9	98.8	100	100	99.45	100	98.12
Effluent Discharge Point	99.9	99.9	100	98.7	100	100	100	100	99.48

Table 2 shows the outcomes of the Photo-Fenton process changed PAH, TOC and degradation percentage in samples. The GC/MS analysis did not find previously known PAHs benzo(a)pyrene, and benzo(k)fluoranthene. The process was effective in degrading the composite materials, particularly the PAHs Benzo(b)pyrene and Benzo(k)fluoranthene, which must be less than 0. 06$\mu g.L^{-1}$ as per CPCB. This is essential to stress these kinds of hydrocarbons were found in the material before the AOP, at levels that exceeded those permissible by law. Supporting the breakdown of these contaminants is critical, as all two PAHs are regarded as hazardous, with benzo(a) pyrene being the most dangerous. The investigation included contamination and PAH being removed and an average TOC content examination also we focus on the effective removal of COD and phenol content from oil-based wastewater. Through AOPs and innovative composite materials, we aim to significantly reduce the concentration of these pollutants. By utilizing tailored treatment methods and novel catalysts, we seek to enhance the degradation efficiency and ensure environmentally sustainable management of oil refinery effluents. Our research endeavors to develop cost-effective and scalable solutions to address the challenges posed by COD and phenol contamination in oil refinery wastewater, contributing to improved environmental stewardship and regulatory compliance within the industry. **Table 2** shows that specimens from many stages were subjected to TOC measurement twice, which matched the outcomes from the treatment plant locations. The circumstances evaluated resulted in partial mineralization of all samples. Boosting the concentration of peroxide or employing InfLU might indicate a need for more vigorous therapy.

The neural network utilized during modeling infallible deep neural networks was the multilayer perceptron (MLP), which included three unique layers, which are input layer (neurons), hidden layer (neurons) and output layer(neuron). The primary strategy technique utilized neurons in the middle layer of neurons and the InfLU activation function in the exit layer. The collected information has been normalized to a range of 0.2 to 0.8 and divided into three categories, which were 80% for training, 10% for testing and 10% for validation. The Levenberg-Marquardt algorithm was used for measurement. **Figure 3** illustrates comparisons between real-world and simulated information for experimental and simulation environments.

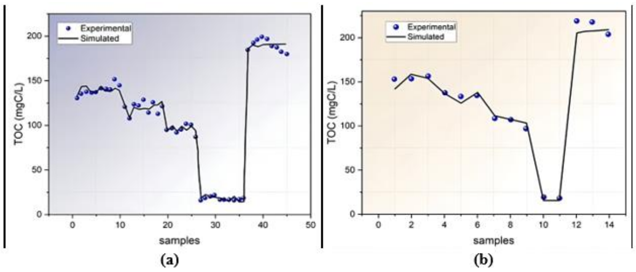


Figure 3: a) Trial, and b) Test were employed for the comparison of experimental and simulated data.

Figures 4 and 5 demonstrate that the neural network that had been trained achieved an excellent level of association for both training (R^2 = 0.998) and testing (R^2 = 0.994) with no consideration of changeable duration.

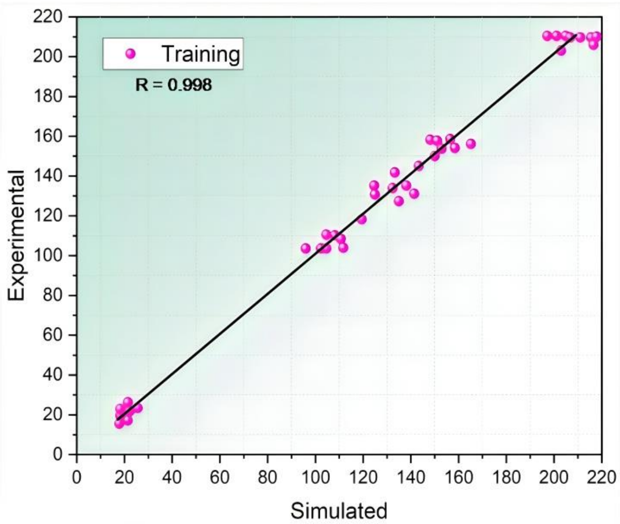


Figure 4: comparing experimental & simulated data for training.

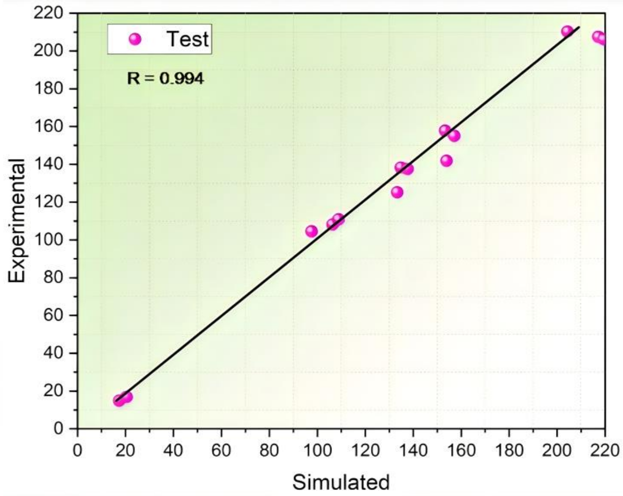


Figure 5: comparing experimental & simulated data for testing.

After obtaining experimental and simulated data for both training and testing, confirmation was utilized for verifying the values' proximity. The neural network accurately tracked the data and its TOC contents. **Figure 6** indicates a correlation coefficient of R^2 = 0.996.

The following phase followed the same approach as the previous stage, which resulted in a successful linear regression with the addition of the variable time. The effectiveness of the framework was evaluated using a chart to determine the optimal training, testing, and validation method. The variable-time modeling technique accurately predicted TOC contents in both experimental and simulated data sets (**Figure 6**). The evaluation, together with the correlation coefficient (R^2 = 0.998), accurately predicted the results of the investigation.

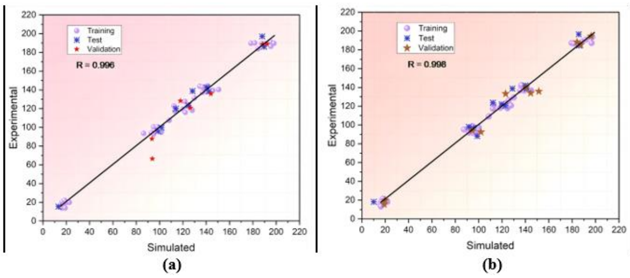


Figure 6: Compares experimental & simulated data for training, testing, and validation

In our work on oil refinery wastewater treatment, we used RMSE graphs to analyze the performance of models. The values of RMSE were plotted with simulation iterations or hyper parameter setups to visually measure prediction accuracy. This helped optimize the therapeutic results and improve comprehension of our suggested methodology's effectiveness. The number of data points is denoted by n, while the observed value is denoted by y_i $\hat{y}_i$ is the model's anticipated value as shown in **Figure 7**.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{4}$$

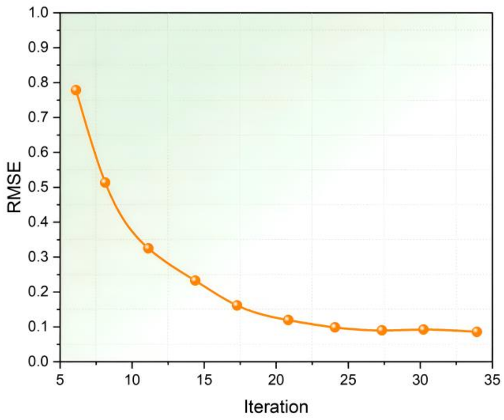


Figure 7: RMSE

In the study on oil refinery wastewater treatment, we used MAE to test the accuracy of predictions. MAE gives an easy way to assess model performance by computing the mean absolute variances of expected and observed values. This allowed us to adjust our strategy for best outcomes and assess the efficacy of our treatment approaches as shown in **Figure 8**.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

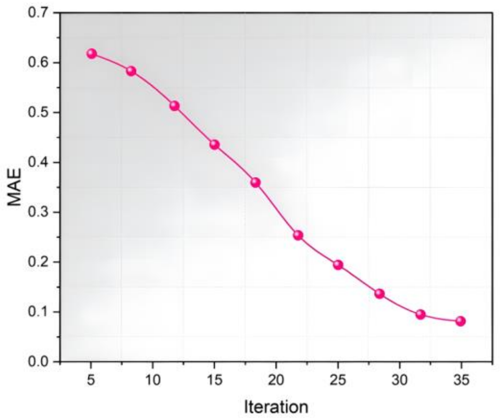


Figure 8: MAE

5. Conclusion

The decomposition of PAHs in every sample studied demonstrates the fact that advanced oxidation processes, used in conjunction with biological processes or on their own, have proven effective for the decomposition of insensitive substances in oil extraction when discussed for most studies, the photo-Fenton technique resulted in rates of 50% to 95% degenerative diseases after a brief training session of up to 20 minutes. Despite having a restricted quantity of data, the period required to treat both neural modeling methodologies tested was found to be more effective when the coefficients of correlation were calculated using data from research, proving the effectiveness of neural network models in demonstrating the AOP. Thus, the InfLU could clarify the complex's achievement as a photo-oxidation procedure by analyzing the ratios of correlation with experimental and simulated data and anticipating the outcome parameters, Oil Content Detector (OCD). The research's limitation is the fact concentrates on enhancing AOP efficiency in treatment with InfDNN, possibly neglecting additional critical elements of extensive wastewater treatment optimization, that include cost-effectiveness, scalability and real-world applicability beyond testing environments. The future objectives of the research will include scaling the InfDNN methodology for applications in real life, investigating its compatibility with different treatment methods and enhancing its effectiveness and economics for general use in oil refinery treatment of wastewater.

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