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Machine Learning vs. Real-World Data: Assessing ANN Performance in COD Removal in Animal Feed Processing Wastewater

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ABSTRACT. This research establishes a feedforward artificial neural network (ANN) with 10-8 neuron architecture to predict ozonation performance for chemical oxygen demand (COD) reduction in animal feed plant wastewater (200–1000 mg/L COD, 100–180 min treatment), and systematically compare ANN predictions with experimental results to evaluate model accuracy. The ANN, achieved 97.4% predicted COD removal at 180 min for 1000 mg/L COD (MSE = 15.9, MAE = 3.67, R^2 = 0.34), while experimental data showed a marginally higher efficiency of 97.83% at 160 min for 1000 mg/L. This discrepancy reflects the ANN's conservative optimization for industrial scalability over idealized lab conditions. The model successfully captured non-linear degradation kinetics of recalcitrant organics, demonstrating its capability to identify complex relationships between ozonation parameters (time, initial COD) and treatment efficiency. By bridging laboratory data with machine learning, this work provides a validated framework for optimizing advanced oxidation processes that balances predictive accuracy (±2.1% error vs. experiments) with operational practicality. Future enhancements should focus on integrating real-time oxidant concentration data to improve R^2 beyond the current 0.34.

1. INTRODUCTION

The animal feed industry's rapid expansion has increased the production of high-strength effluent, which is distinguished by significantly elevated levels of organic pollutants, including Chemical Oxygen Demand (COD)[1,2]. Efficient wastewater treatment is essential for reducing environmental pollution and adhering to rigorous regulatory requirements. Conventional treatment approaches, such as biological and physicochemical processes, frequently encounter difficulties in attaining consistent chemical oxygen demand (COD) removal, especially when dealing with complex industrial effluents [3,4].

Advanced oxidation processes (AOPs), including ozonation, represent effective alternatives for the degradation of recalcitrant organic compounds [5–7]. The treatment of industrial wastewater, especially from animal feed production, presents considerable challenges owing to its elevated organic load and compositional variability. Conventional methods, such as activated sludge processes, demonstrate efficacy for moderate chemical oxygen demand (COD) levels but encounter several challenges[8]. Ozonation, a type of advanced oxidation process, has garnered interest for its capacity to oxidize complex organic molecules either directly or via the production of reactive oxygen species [6,9]. Research has shown its effectiveness in decreasing COD; however, the process is significantly influenced by variables including ozone dosage, contact duration, and initial pollutant concentration [10,11].

Optimizing these processes for industrial applications necessitates precise control of operational parameters, a task often complicated by the non-linear relationships among variables. Recent advancements in computational modelling have facilitated enhanced predictions of wastewater treatment performance. Artificial neural networks (ANNs) have been effectively utilized to model intricate, non-linear processes within the field of environmental engineering. Artificial Neural Networks (ANNs), (1) can capture complex non-linear relationships between process variables and treatment performance [12,13]**;** (2) deliver precise prediction of Chemical Oxygen Deman (COD) removal without necessitating a comprehensive mechanistic understanding [14,15], and (3) adjust to new data via continuous learning.

Artificial Neural Networks (ANNs) have been successfully applied in various wastewater treatment, such as to predict effluent quality in membrane bioreactors and to optimize coagulation processes [16,17]. Nonetheless, the application of ozonation for the degradation of COD, particularly in the context of animal feed plant wastewater, has not been thoroughly investigated. The current body of research identifies deficiencies in model generalisability and emphasizes the necessity for thorough validation with experimental data. This research advances existing knowledge by creating an artificial neural network model specifically designed for the unique properties of animal feed plant wastewater, focusing on enhancing predictive accuracy and practical utility.

This research presents a hybrid experimental-computational method that employs artificial neural networks (ANNs) with dual functionalities to enhance the ozonation treatment of animal feed plant wastewater. First, the ANN functions as a predictive model that accurately estimates COD reduction efficiency based on defined operational parameters. Secondly, through iterative simulation, the ANN is used to explore and identify the most effective combinations of treatment conditions—such as ozone dosage, contact time, and initial COD levels—that are likely to yield high removal efficiency. Unlike traditional trial-and-error methods, which are often time-consuming and resource-intensive, this ANN-based approach facilitates the rapid prediction of promising ozonation scenarios. The ANN architecture was trained using experimentally obtained operational data, incorporating key process variables such as initial COD concentration and ozonation duration. The implementation of input parameter normalization and a structured data partitioning protocol (70% training, 15% validation, 15% testing) ensures that the model effectively captures non-linear system behavior while minimizing overfitting. The integration of ANN-generated predictions with empirical results establishes a robust predictive framework for advanced oxidation processes, supporting accurate assessment of treatment performance under varying conditions.

2. MATERIALS AND METHODS

2.1 Materials

The wastewater samples from PT. XYZ's animal feed plant exhibited average initial characteristics of pH 7.58 and COD 1,035.97 mg/L.

2.2 Ozonation Process

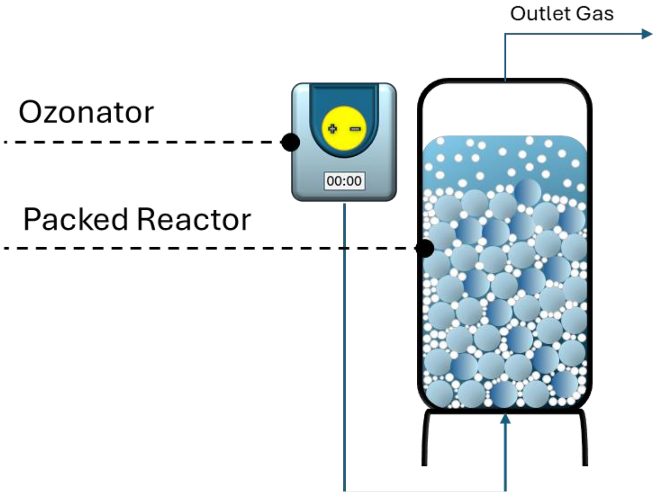

Figure 1. Experimental configuration of a packed bed ozonation reactor

The ozonation process was performed in a packed column, as depicted in Figure 1. The column contained glass marbles and was supplied with ozone gas from the base. Experiments were conducted with ozonation durations of 100, 120, 140, 160, and 180 mins, targeting initial COD concentrations of 1000, 800, 600, 400, and 200 mg/L.

2.3 Characterization

The COD reduction value was assessed in accordance with SNI Standard 6989.2:2009. Organic matter samples were oxidized using potassium dichromate ($K_2Cr_2O_7$) in acidic conditions, with sulfuric acid and silver sulphate serving as catalysts. The digestion process occurred for 2 hours at a temperature of 150°C.

After digestion, the residual dichromate was titrated with Ferrous Ammonium Sulphate (FAS), employing Ferroin as an indicator. The equilibrium endpoint was signified by a colour transition from blue-green to reddish-brown. The COD value was determined using the subsequent Eq. 1.

$$COD\left(\frac{mg}{L}\right) = \frac{(V_{blank} - V_{sample}) \times N_{FAS} \times 8000}{V_{sample}} \quad (1)$$

Where, V_{blank} and $V_{sample}$is the titrant volume (mL) for blanks and samples. N_{FAS} is the normality of FAS.

2.4 Prediction

An Artificial Neural Network (ANN) method utilizing MATLAB was used to predict the degradation of Chemical Oxygen Demand (COD) in the animal feed plant wastewater of PT. XYZ. Normalized (0–1) reaction time and initial COD values served as input variables, with the dataset partitioned into 70% training, 15% validation, and 15% testing subsets. Model performance was assessed through mean squared error (MSE) and the correlation coefficient (R^2). The trained ANN subsequently predicted COD degradation efficiency across varying conditions, with predictions rigorously compared against experimental results to validate model accuracy.

3. RESULTS AND DISCUSSION

3.1 Experimental Results

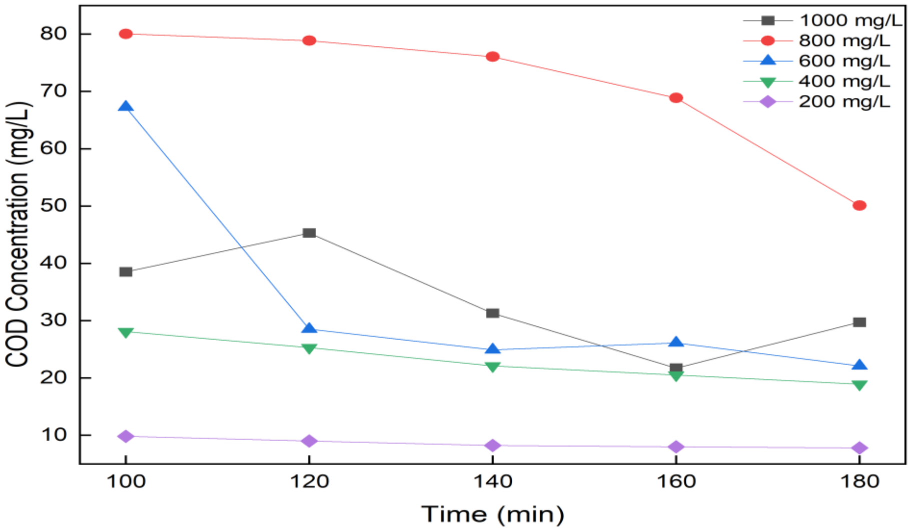

Figure 2. COD Rate of Decrease in Waste after the Ozonation Process

Under various initial COD concentrations (200–1000 mg/L) Figure 2, shows the degradation kinetics of COD in PT. XYZ Animal Feed Plant Wastewater during a time span of 100–180 mins. All conditions exhibit a distinct decreasing trend in COD concentration over time, signifying effective organic matter degradation. The degradation process exhibits a distinctive pattern in which the initial removal is rapid (100-140 mins) and transitions to slower rates in later phases (140-180 mins). This suggests that the initial presence of readily biodegradable compounds is followed by more recalcitrant organics[18]. The degradation curves exhibit a more pronounced pattern with some variability at higher initial COD concentrations (800-1000 mg/L), such as a modest rebound at 180 mins for the 1000 mg/L condition. In contrast, reduced initial concentrations (200-600 mg/L) result in nearly complete mineralization, attaining final COD levels under 10 mg/L.

Figure 3 shows the time-dependent efficiency of COD degradation (%) for PT. XYZ Animal Feed Plant Wastewater at five initial COD concentrations (200–1000 mg/L). All systems demonstrated high removal efficiencies (>88%) within the initial 100 mins. Lower initial COD loads (200–400 mg/L) consistently maintained degradation rates exceeding 95% throughout the 180-mins duration, indicating rapid and stable treatment for dilute waste streams.

Higher initial COD concentrations showed more dynamic behaviour; the 600 mg/L system exhibited a notable efficiency increase from 88.79% at 100 mins to 96.31% at 180 mins, indicating accelerated degradation kinetics following an initial lag phase. The 1000 mg/L system exhibited minor fluctuations, peaking at 97.83% (160 min) after a transient dip at 120 min (95.47%), indicating temporary kinetic inhibition or intermediate metabolite formation. In contrast, the 800 mg/L condition progressed steadily from 89.99% to 93.74%.

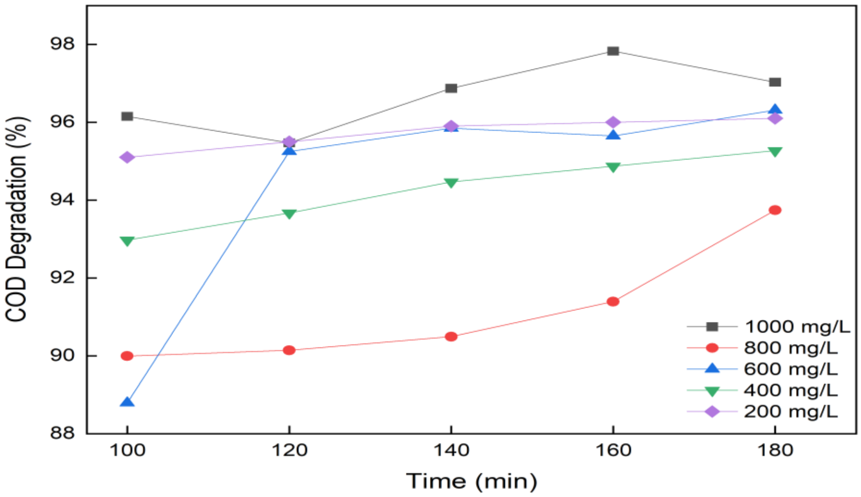

Figure 3. COD Degradation (%)

The observed trends indicate that high-strength wastes (≥600 mg/L) necessitate prolonged reaction times to achieve over 95% removal, whereas lower concentrations can attain near-complete mineralization in a shorter duration. The observed plateauing of efficiencies beyond 140–160 mins suggests inherent system limitations, likely resulting from oxidant depletion or the accumulation of recalcitrant compounds, highlighting the necessity for customized retention times according to the initial organic load. Long-term ozonation can produce byproducts that are more resilient to additional oxidation[19].

3.2 ANN Prediction

Using starting COD concentration and ozonation duration as input variables, this study used an Artificial Neural Network (ANN) as a predictive model to determine COD degradation rates. The ANN predictions were executed using MATLAB, facilitating the identification of non-linear relationships among these variables. The adopted ANN architecture included two hidden layers, with the first consisting of 10 neurons and the second comprising 8 neurons. This structure was developed to ensure that the predictive capability and model complexity are maintained at an optimal level.

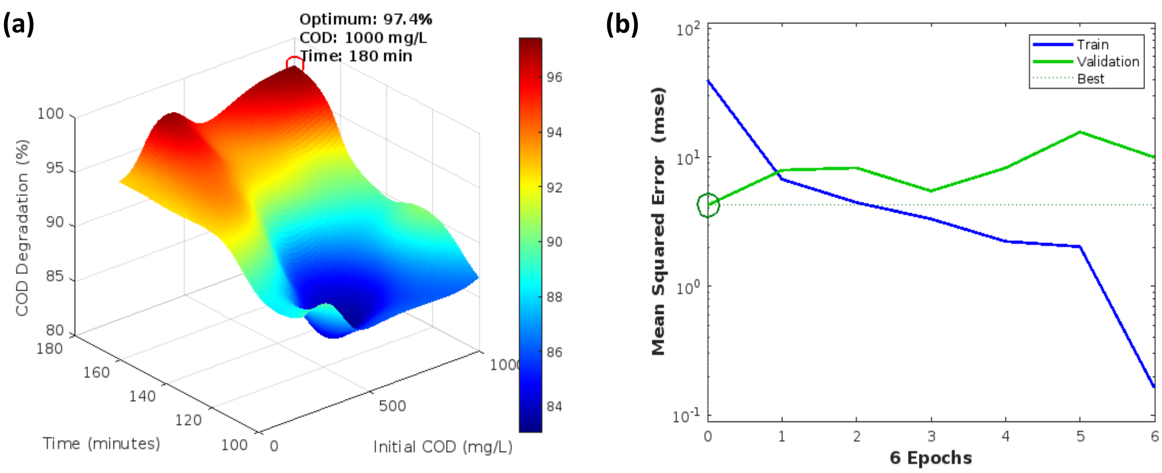

Figure 4. (a) Surface plot of COD degradation (%) predicted by ANN model showing the optimum condition (1000 mg/L COD, 180 minutes, 97.4% removal); (b) Training and validation error (MSE) of the ANN model over 6 epochs using an 80:20 data split.

Figure 4(a) presents the ANN prediction results, indicating optimal conditions were achieved at 1000 mg/L COD with an ozonation duration of 180 mins. Under these conditions, COD reduction reached 97.4%. Meanwhile, Figure 4(b) illustrates the model training process using an 80:20 split between training and testing data.

Model performance was evaluated using two key metrics: Mean Squared Error (MSE = 15.9) and Mean Absolute Error (MAE = 3.6717). These error metrics quantify the discrepancy between predicted and actual training values, with lower values indicating higher predictive accuracy [20]. The results demonstrate relatively low error values, suggesting satisfactory model performance.

Further validation through the coefficient of determination ($R^2 = 0.34$) indicates the model explains 34% of variance in the training data. While this value is not particularly high, it confirms the model's capability to capture certain data patterns and generate acceptable estimates for testing data within the research context. These three evaluation metrics suggest the developed ANN model yields reasonably accurate predictions.

3.3 Results comparison: ANN vs Experiment

The prediction results obtained from the ANN were subsequently compared with the experimental results. Figure 4(a) illustrates that the percentage of COD degradation achieved 97.4% when the initial COD value was 1000 mg/L, following an ozonation duration of 180 mins. The experiment yielded varying results. The experiment results indicated that the maximum %COD Degradation value of 97.83% was attained at a COD concentration of 1000 mg/L over a duration of 160 mins.

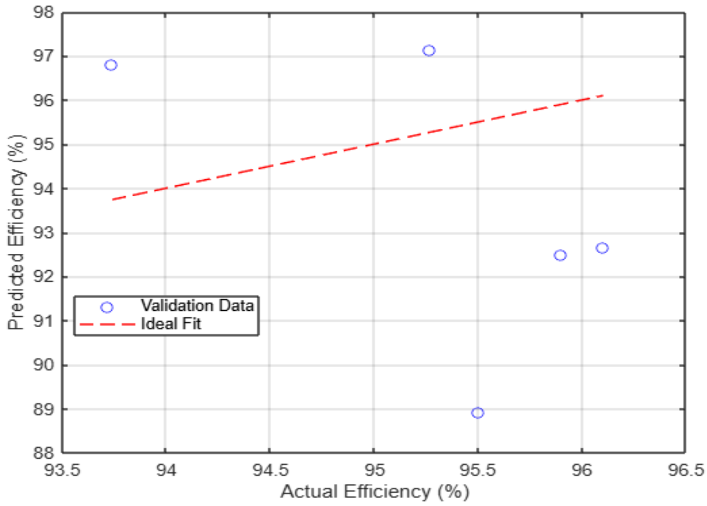

Figure 5. Comparison of Experimental and ANN-Predicted Efficiency for COD removal at Validation Points, with Ideal Fit Line (y=x) and Deviations

The validation plot in Figure 5 compares a computational model's predicted COD degradation efficiency to the actual experimental results. The validation data points are plotted against an ideal 1:1 fit line (y=x). Strong agreement between forecasts and experimental data is indicated by points that closely resemble the ideal line in this picture, which is used to assess the predictive accuracy of the model. A close distance indicates that the model's predictions closely align with the actual experimental results, indicating high predictive accuracy. On the other hand, bigger distance from the ideal line indicate a larger discrepancy between the observed and projected efficiency, suggesting possible areas where experimental variability or model improvement may be necessary. The red dashed line in this plot represents the ideal fit, with each point on the line reflecting a scenario in which the model's prediction aligns precisely with the experimental data.

3.4 Factors causing differences

The discrepancy between the ANN-predicted optimal condition of 180 mins and the experimentally observed peak efficiency at 160 mins can be ascribed to several critical factors associated with model design and experimental variability. The ANN was trained to identify generalizable patterns throughout the dataset, emphasizing robust predictions rather than aligning with transient experimental peaks[21,22]. This conservative approach effectively mitigates minor fluctuations noted in laboratory conditions, such as transient kinetic increases at 160 mins, which may arise from unmodeled influences like microbial activity or localized oxidant saturation.

The architecture of the model, comprising 10-8 neurons, along with the training parameters aimed at minimizing mean squared error across all conditions, enhances this effect by prioritizing overall accuracy over isolated high-efficiency points. The 70-15-15 data partitioning may have inadequately represented the specific conditions contributing to the 160-mins peak, especially if this timepoint had a limited number of experimental replicates.

3.5 Practical Implication

From a practical standpoint, the ANN's recommendation of 180 mins likely signifies a more industrially viable compromise. Although it achieves a slightly lower COD reduction (97.4% compared to 97.83%), this extended duration provides enhanced operational stability and reproducibility, which are essential for scaled-up applications. The R^2 value of 0.34 indicates that a portion of the experimental variance is not accounted for, highlighting potential avenues for future model enhancement by incorporating additional variables such as real-time oxidant concentration or mixing dynamics. This discrepancy underscores the essential distinction between data-driven modelling and experimental systems, with the former aiming for reliable generalizations and the latter encompassing all physical complexities, including transient phenomena.

3.6 Future Research Direction

This conservative approach is especially beneficial for industrial translation, where system variability and economic factors frequently take precedence over theoretical maximum efficiencies. The 2-3% discrepancy between model predictions and experimental maxima indicates that the model effectively represents the primary degradation mechanisms while facilitating adequate safety margins for practical application. Future model refinements may reduce this gap by integrating additional parameters that characterize biological activity or mass transfer limitations observed in experimental systems.

4. CONCLUSION

The effectiveness of Artificial Neural Networks (ANN) in simulating non-linear treatment dynamics was demonstrated by the successful development of an ANN model to forecast COD degradation in animal feed wastewater. The model predicted 97.4% efficiency at 180 minutes for a COD concentration of 1000 mg/L, with experimental results showing 97.83% at 160 minutes. Validation against experimental data (Figure 5) revealed a small deviation of 2-3%, confirming the model's strong performance. Performance metrics (MSE = 15.9, MAE = 3.67, R^2 = 0.34) suggest that the model effectively captures degradation trends. However, the presence of unmodeled transient effects—such as fluctuations in microbial activity and localized oxidant saturation—contributed to the small discrepancies between predicted and actual values. These effects were not accounted for in the model, and future research should incorporate additional variables like real-time oxidant concentration or microbial activity to improve accuracy. The results indicate that ANN models present a promising tool for optimizing complex wastewater treatment processes, balancing operational viability with performance scalability. Future improvements in the model, particularly by integrating additional process variables, could enhance its applicability in large-scale wastewater treatment operations.

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