Galore International Journal of Applied Sciences and Humanities
Vol. 8; Issue: 2; April-June 2024
Website: www.gijash.com
Review Paper *P-ISSN: 2456-8430*

Artificial Neural Networks for Modeling Pollutant Removal in Wastewater Treatment: A Review

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DOI: https://doi.org/10.52403/gijash.20240211

ABSTRACT

Water pollution poses global challenges to environmental sustainability and public health, necessitating effective wastewater treatment strategies. Traditional linear models often fail to capture the complexities of pollutant removal processes. Artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) have emerged as powerful tools for modeling and optimizing wastewater treatment. ANNs excel in learning complex patterns and nonlinear relationships, while ANFIS integrates neural network learning with fuzzy logic to handle uncertainties in environmental systems. Case studies demonstrate their efficacy in predicting pollutant removal efficiencies, with ANFIS consistently outperforming traditional methods. Insights into influential factors like pH and pollutant concentration guide process optimization. The review underscores ANNs and ANFIS' potential to enhance wastewater treatment efficiency, reduce costs, and ensure regulatory compliance, paving the way for sustainable water management practices.

Keywords: Artificial neural networks; Adaptive neuro-fuzzy inference systems; Modelling; Wastewater

INTRODUCTION

Water pollution is an escalating global concern that threatens environmental sustainability, public health, and economic prosperity. The pervasive contamination of water bodies by pollutants from industrial, agricultural, and domestic sources results in the degradation of water quality and the disruption of aquatic ecosystems. Pollutants such as heavy metals, organic compounds, nutrients, and pathogens can have dire consequences on human health and biodiversity if left untreated [1]. Consequently, effective wastewater treatment and pollutant removal are critical to safeguarding water resources and ensuring compliance with stringent environmental regulations.

In recent years, the complexity and variability of wastewater treatment processes have posed significant challenges for traditional modeling and optimization techniques. Conventional approaches, often based on linear assumptions, fall short in accurately capturing the nonlinear dynamics and multifaceted interactions inherent in these processes [2]. As a result, there has been a growing interest in the application of advanced computational techniques that can address these limitations and enhance the efficiency and reliability of wastewater treatment systems.

Artificial Neural Networks (ANNs) have emerged as a promising solution to these challenges. Inspired by the neural architecture of the human brain, ANNs are computational models that consist of interconnected layers of nodes (neurons) [3]. These networks are capable of processing large datasets, learning complex patterns, and making highly accurate predictions. The strength of ANNs lies in their ability to adaptively learn from data, thereby modeling intricate and nonlinear relationships that are often present in environmental systems [4]. The application of ANNs in environmental science is diverse, ranging from climate modeling and air quality prediction to hydrological forecasting and ecosystem management. In the realm of water treatment, ANNs have been utilized for various purposes, including predicting effluent quality, optimizing operational parameters, and real-time system monitoring [5]. Their flexibility and robustness make ANNs particularly well-suited for modeling pollutant removal processes in aquatic systems, where numerous interdependent factors influence treatment outcomes.

The process of pollutant removal in water treatment systems involves a series of complex physical, chemical, and biological interactions. These processes are influenced by a multitude of factors, including the type and concentration of contaminants, the characteristics of the treatment medium, operational conditions, and environmental variables [6]. Traditional modeling techniques often struggle to account for these multifaceted interactions, leading to suboptimal predictions and inefficiencies in treatment operations. ANNs address these challenges by leveraging their powerful learning algorithms to identify and model the underlying patterns in historical data. By training on extensive datasets, ANNs can capture the intricate relationships between input variables and treatment outcomes, enabling more accurate and reliable predictions [7]. This capability is particularly valuable for optimizing treatment processes, as it allows for the fine-tuning of operational parameters to achieve maximum efficiency and effectiveness.

The advantages of using ANNs for modeling pollutant removal in aquatic systems are manifold [8]. Firstly, ANNs provide superior predictive accuracy compared to traditional models, which translates into better process control and optimization. This improved accuracy helps in reducing operational costs, enhancing treatment efficiency, and ensuring compliance with regulatory standards. Secondly, ANNs possess the ability to continuously learn and adapt as new data becomes available, making them highly responsive to changing conditions and emerging challenges in water treatment. Lastly, the use of ANNs can facilitate the integration of real-time monitoring and control systems, enabling proactive management of treatment processes and timely interventions to address potential issues [9].

This comprehensive review delves into the application of ANNs for modeling pollutant removal in wastewater. It begins with an overview of water pollution and the necessity of effective wastewater treatment. Following this, the principles and structure of ANNs are discussed, along with their general applications in environmental modeling. The review then focuses on the specific application of ANNs in modeling pollutant removal, highlighting case studies and examples from recent research. Finally, the review examines the benefits, challenges, and prospects of employing ANNs in this context, aiming to provide a thorough understanding of their potential to revolutionize water quality management and contribute to sustainable environmental practices.

By synthesizing current knowledge and advancements in this field, this review aspires to underscore the critical role of ANNs in addressing the complexities of pollutant removal in aquatic systems, paving the way for more efficient, adaptive, and sustainable wastewater treatment solutions.

OVERVIEW OF ANN ARCHITECTURE

The concept of artificial neurons was initially proposed in 1943 by McCulloch and Pitts. However, it was not until the introduction of the back-propagation training (BP) algorithm for feedforward ANNs in 1986 by Rumelhart et al. that the practical applications of ANNs in research areas began to gain significant traction [10]. Essentially, an ANN functions as an information processing system designed to mimic, to some extent, the behavior of the human brain. This emulation is achieved by simulating the operations and interconnectivity observed in biological neurons. Research on the human brain reveals that it comprises approximately 10^{11} biological neurons involved in around 10^{15} connections across neural pathways. Each pathway extends over a meter in length. Neurons share common characteristics with other cells in the body but possess unique abilities to receive, process, and transmit electrochemical signals along neural pathways, forming the brain's communication system. Each biological neuron consists of three basic components:

- Dendritic branches: Receive incoming signals to the cell body.
- Cell body: Synthesizes and processes signals for outgoing transmission.
- Axon fibers: Transmit signals from the cell body to other neurons.

Dendritic branches relay signals to the cell body, which processes and emits outgoing signals. Axon fibers transmit signals from this cell body to other neurons. The point of connection between the axon fiber of one neuron and the dendritic branch of another is called a synapse. The connections between neurons and the sensitivity of each synapse are determined by complex chemical processes. Some neuron structures are predetermined before birth, while others develop through learning processes. Throughout an individual's lifespan, new connections form while others are eliminated.

Biological neurons operate as follows: they receive incoming signals, process them, and produce an output signal. This output signal then serves as input for other neurons. Drawing from insights into biological neurons, humans have developed artificial neurons intending to create a model comparable in strength to the human brain, as described in Fig. 1.

A neuron is an information processing unit and a fundamental component of a neural network. The structure of a neuron is depicted as shown in Figure 1b. The fundamental components of an artificial neuron encompass the input set, weight set, summing function, bias (threshold), transfer function, and output. The input set consists of input signals, typically organized as a vector of N dimensions. Each connection is represented by a weight, denoted as synaptic weight, which is randomly initialized and continuously updated during network learning. The summing function computes the sum of the products of inputs and their corresponding synaptic weights. A bias, also known as a threshold, is incorporated into the transfer function. This function limits the output range of each neuron, typically within the interval [0, 1] or [-1, 1]. Transfer functions vary, ranging from linear to nonlinear, and the choice depends on the specific problem and the designer's experience. The output is the resulting signal from a neuron, with each neuron having a maximum of one output.

There are three types of ANN architectures: single-layer, multi-layer, and competitive-layer. These architectures can be classified based on their training methods into supervised, unsupervised, and hybrid categories [11]. Multi-layer architectures typically use supervised training methods, whereas competitive-layer architectures employ unsupervised training techniques. Among the most well-known supervised learning algorithms are backpropagation and learning vector quantization. In contrast, unsupervised methods include self-organizing maps (SOM) and radial basis function (RBF) algorithms [12].

A multi-layer perceptron architecture can be trained using various algorithms, such as backpropagation, Levenberg-Marquardt, and quasi-Newton algorithms. Among these, the multi-layer architecture employing the backpropagation learning algorithm is particularly notable for its robust predictive capabilities [13]. This model utilizes a supervised learning method, wherein the backpropagation algorithm adjusts the synaptic weights based on the error output propagated in the reverse direction. To determine this error, a forward propagation step is performed initially, where the input data passes through the network layers to generate an output. The error, defined as the difference between the predicted and actual outputs, is then calculated. The backpropagation algorithm iteratively updates the weights to minimize this error, enhancing the model's accuracy over successive iterations. The architecture of a multi-layer perceptron, as illustrated in Figure 1, demonstrates the intricate interplay between input, hidden, and output layers, showcasing the complex yet efficient process of error correction and weight adjustment that underpins the learning process in artificial neural networks. This architecture's adaptability and precision make it a valuable tool in various predictive applications, from pattern recognition to complex data modeling, emphasizing its significance in advancing computational intelligence.

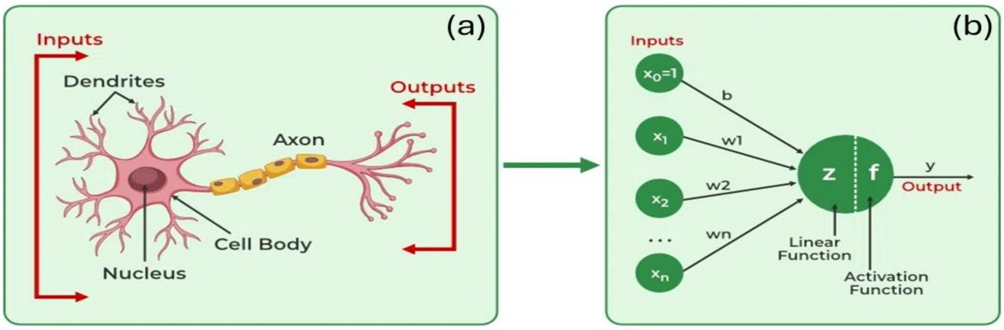

Figure 1 - Transition from Biological Neurons (a) to Artificial Neurons (b) (Sourced from https://www.geeksforgeeks.org)

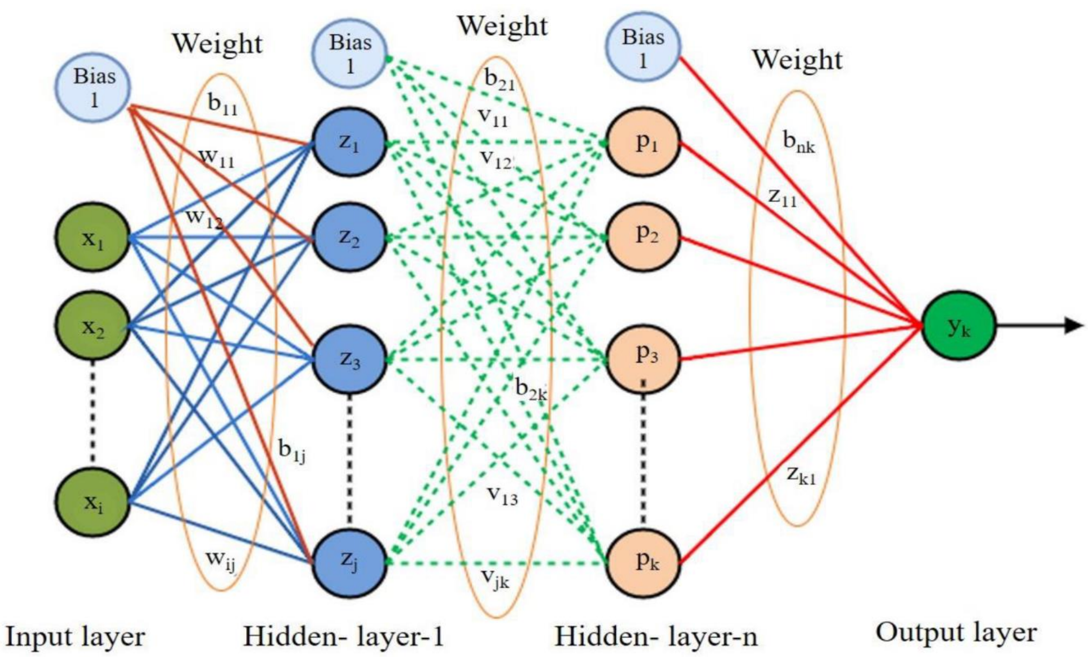

Figure 2 – The architecture of a typical multi-layer neural network [14].

APPLICATION OF ANNS FOR MODELING POLLUTANT REMOVAL IN WASTEWATER

Applications of ANNs have shown considerable promise in predicting optimal conditions for the degradation and mitigation of pollutants in wastewater, often delivering relatively high performance. The utilization of ANNs for such predictive tasks typically involves a variety of training algorithms, with backpropagation being one of the most commonly employed. This algorithm is known for its robust prediction capabilities, making it a popular choice in many studies [15,16]. However, a significant drawback of the backpropagation algorithm is its relatively slow training speed, which can be a limitation in time-sensitive applications [17]. To address this issue, several subsequent studies have explored the use of the Levenberg-Marquardt (LM) training algorithm within ANNs. The LM algorithm is particularly noted for its faster training capabilities compared to other methods. It not only accelerates the convergence process but also often yields better performance outcomes. The speed and efficiency of the LM algorithm make it a compelling alternative to traditional backpropagation, especially in scenarios requiring rapid and accurate model training [18]. In addition to these methods, model development can also integrate fuzzy logic approaches, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS). ANFIS combines the learning capabilities of neural networks with fuzzy logic principles, enhancing the model's ability to handle uncertainties and nonlinearities inherent in environmental data. For instance, Porhemmat et al. [19] have successfully implemented ANFIS to refine the predictive accuracy and robustness of their pollutant removal models. This hybrid approach leverages the strengths of both neural networks and fuzzy logic, offering a more comprehensive tool for environmental modeling and optimization. The integration of advanced training algorithms like LM and hybrid models like ANFIS represents a significant advancement in the application of ANNs for wastewater treatment. These innovations not only improve the speed and accuracy of pollutant removal predictions but also contribute to the development of more efficient and sustainable environmental management practices.

Biological and physical treatments in wastewater treatment plants are critical variables in water quality management and planning. However, these processes are challenging to quantify and require substantial time to yield precise results. To address these issues, scientists have explored various solutions, among which artificial intelligence models have emerged as a promising approach [20]. These models facilitate more consistent and economical monitoring of pollutant parameters at treatment plants and assist in regulating these pollution elements during processing. Alnajjar and colleagues have proposed using the ANFIS model to regulate primary and biological wastewater treatment processes [21]. The ANFIS model was employed to simulate the nonlinear interactions between influent pollutant factors and effluent variables within a wastewater treatment facility. Specifically, models were developed to predict the removal efficiency of Biological Oxygen Demand (BOD), Total Nitrogen (TN), Total Phosphorus (TP), and Total Suspended Solids (TSS). The input variables for the BOD, TN, TP, and TSS models—Hydraulic Retention Time (HRT), temperature (T), and dissolved oxygen (DO)—were selected based on linear correlation matrices between the input and output variables. In this study, the modeling employed MATLAB APPDESIGNER model data for training, testing, and predictions. The data generated from the APPDESIGNER model used to develop eleven distinct ANFIS models are illustrated in Figure 3. The obtained results demonstrate that the ANFIS model accurately predicts and controls treatment outcomes. The minimum mean square errors achieved by the ANFIS model were 0.1673 for BOD, 0.0266 for TN, 0.0318 for TP, and 0.0523 for TSS. Additionally, the correlation coefficients for BOD, TN, TP, and TSS were notably strong, indicating robust predictive performance.

Figure 3 – APPDESIGNER model interface [21]

In the other study, Mahshidnia M and Jafarian A. used ANFIS to forecast the treatment of wastewater containing Malachite Green – a toxic substance and the comparison between the model's predictions and experimental data validated the process [22]. Accordingly, the ANFIS intelligent model was implemented in MATLAB, comparing three different structures: ANFIS-GP, ANFIS-SUB, and ANFIS-FCM. The ANFIS-SUB structure was selected and trained using two methods: backpropagation (BP) and hybrid. The forecasting scheme is illustrated in Figure 4. The model was trained with 70% of the actual data and evaluated with the remaining 30%. The forecasted results were then compared to the actual values. Error value histograms indicated that the hybrid method yielded superior results. The performance difference between the ANFIS output and the real data during both the training and testing stages was minimal. The high overlap of diagrams in the hybrid method confirmed that the subtractive clustering-based structure of the ANFIS trained by the hybrid method provided better results. The study demonstrated that this approach could accurately forecast the removal percentage of Malachite Green and could be applied to similar scenarios after appropriate training [22].

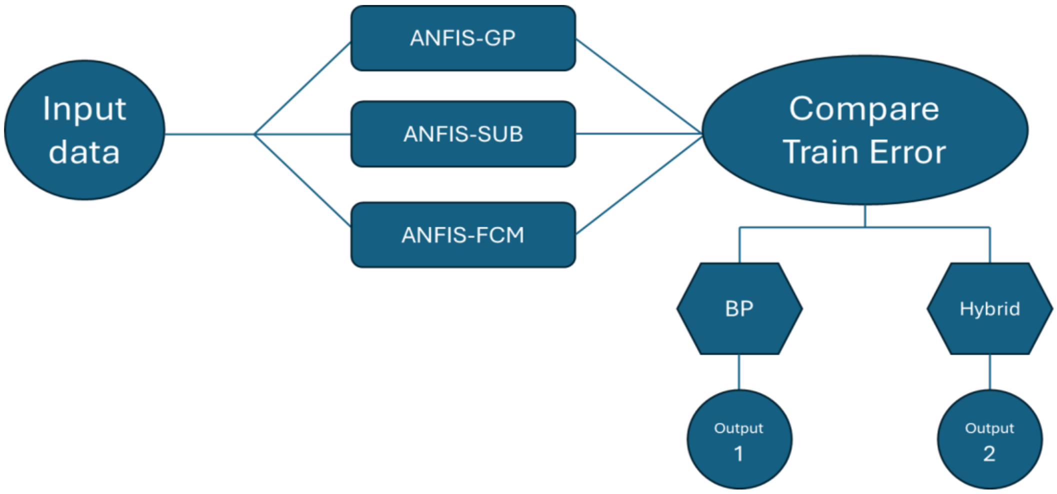

Figure 4 – The furcating scheme [22]

Sridevi H. and coworkers investigated the modeling of the removal of the widely used agricultural herbicide 2,4-Dichlorophenoxyacetic acid (2,4-D) utilizing polypyrrole-coated Fe2O3 nanoparticles (Fe2O3@PPy) [23]. The Fe2O3@PPy nanocomposite was synthesized by surface-coating Fe2O3 nanoparticles, which were synthesized using Tabebuia aurea leaf extract, with polypyrene. Characterization of the nanocomposite was followed by an examination of its adsorptive potential for removing 2,4-D from aqueous solutions. Optimization of the adsorption process was carried out using Central Composite Design (CCD), achieving an adsorption efficiency of 90.65% at a 2,4-D concentration of 12 ppm, a dosage of 3.8 g/L, an agitation speed of 150 rpm, and a contact time of 196 minutes. The adsorption data conformed well to the Langmuir isotherm (R^2: 0.984, χ^2: 0.054) and pseudo-second-order kinetics (R^2: 0.929, χ^2: 0.013), with thermodynamic studies confirming the exothermic and spontaneous nature of the adsorption process. Predictive models including ANFIS, ANN, and response surface methodology (RSM) exhibited high precision in predicting 2,4-D adsorption (Table 1). Accordingly, RSM, a statistical technique for designing experiments, building models, and evaluating the effects of several variables, demonstrated a predictive R^2 value of 0.9528. Despite its efficacy in optimizing process parameters, RSM was found to be the least effective among the three models in terms of prediction accuracy.

ANN, inspired by biological neural networks, was utilized to model the nonlinear relationships between input parameters and adsorption efficiency. The ANN model achieved a higher predictive R^2 value of 0.9604, indicating better performance compared to RSM. This model is known for its robustness in handling complex and nonlinear data patterns.

ANFIS, which combines neural network adaptive capabilities and fuzzy logic qualitative approach, emerged as the most precise predictive tool with an R^2 value of 0.9719. The ANFIS model effectively captured the complex interactions among variables, providing superior prediction accuracy and reliability.

Table 1 - Comparison of RSM, ANN, and ANFIS models [23]

Method	Performance parameters			
	R_2	MAE	MSE	RMSE
RSM	0.9528	0.1053	0.0157	0.1251
ANN	0.9604	0.0584	0.0101	0.1007
ANFIS	0.9719	0.0456	0.0071	0.0839

The statistical indices are further represented using a Taylor Diagram (Fig. 5) to facilitate a comparative evaluation of the various models against the experimental datasets. As depicted in Fig. 5, both the ANFIS and ANN models exhibit high correlations. This indicates strong predictive accuracy and reliability in modeling the adsorption efficiency of 2,4-Dichlorophenoxyacetic acid onto polypyrrole-coated Fe_2O_3 nanoparticles.

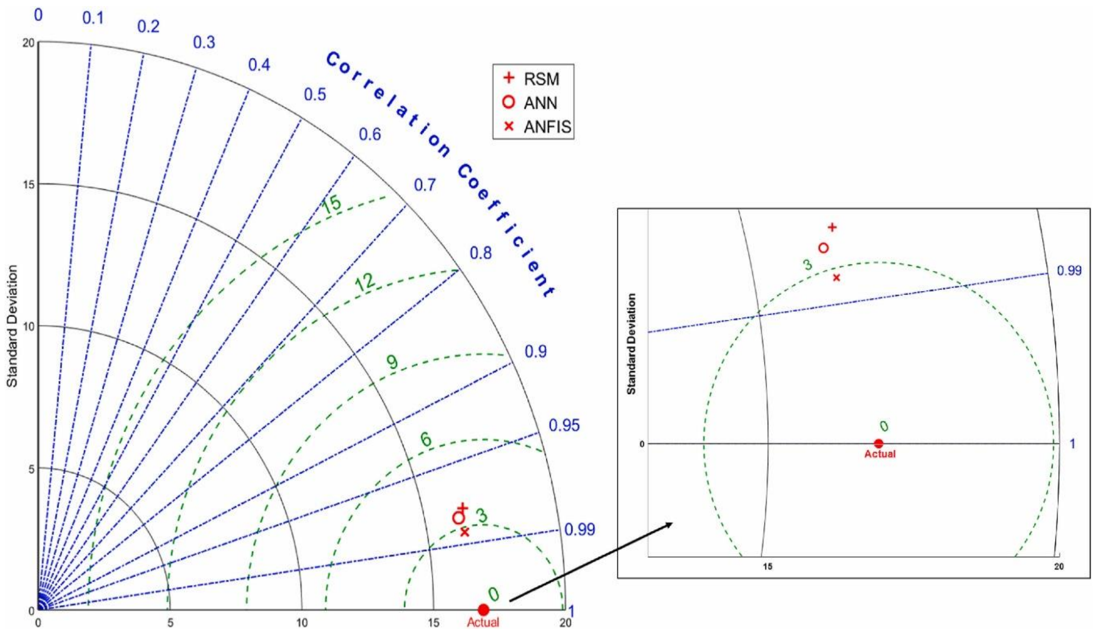

Figure 5 - Taylor Diagram of the Developed RSM, ANN, and ANFIS models [23]

Statistical analysis indicated that ANFIS was the most accurate forecasting tool, while RSM was the least effective. The maximum adsorption capacity of 2,4-D onto the Fe_2O_3@PPy nanocomposite was determined to be 7.29 mg/g, which is significantly higher than several reported values. Consequently, the Fe_2O_3@PPy nanocomposite demonstrates significant potential as an efficient adsorbent for the removal of 2,4-D herbicide from aqueous streams.

In another study, a novel ANN model was developed to predict the adsorption efficiency of arsenate (As (III)) from contaminated water. This model was refined through the analysis of various architectures of an ANFIS, which allowed for a sophisticated approach to model the adsorption process [24].

The database for the current study comprised extensive experimental data on the adsorption of As (III) by different adsorbents and biosorbents. This dataset was meticulously prepared and then randomly divided into two sets to ensure robust model training and validation. Specifically, 70% of the data was allocated to the training phase, allowing the model to learn and adjust its parameters effectively, while the remaining 30% was reserved for the testing phase to evaluate the model's performance and generalizability. Four key statistical evaluation metrics were employed to assess the performance of the ANFIS models: mean square error (MSE), root-mean-square error (RMSE), Pearson's correlation coefficient (R%), and the determination coefficient (R^2). These metrics provided a comprehensive evaluation of the model's accuracy and predictive capability. The results indicated that the best performing ANFIS model achieved impressive average values of 97.72% for R%, 0.9333 for R^2, 0.137 for MSE, and 0.274 for RMSE. These high-performance metrics underscore the model's robustness and its potential application in practical scenarios [24].

Furthermore, a detailed parametric investigation was conducted to identify the factors that most significantly influence the adsorption process efficiency. The study revealed that pH, initial concentration of arsenic, contact time, adsorbent dosage, inoculum size, and temperature were the predominant parameters affecting the adsorption efficiency, listed in descending order of impact (Figure 6). These insights are crucial for the scale-up and optimization of the adsorption process, providing valuable guidance for future research and practical applications.

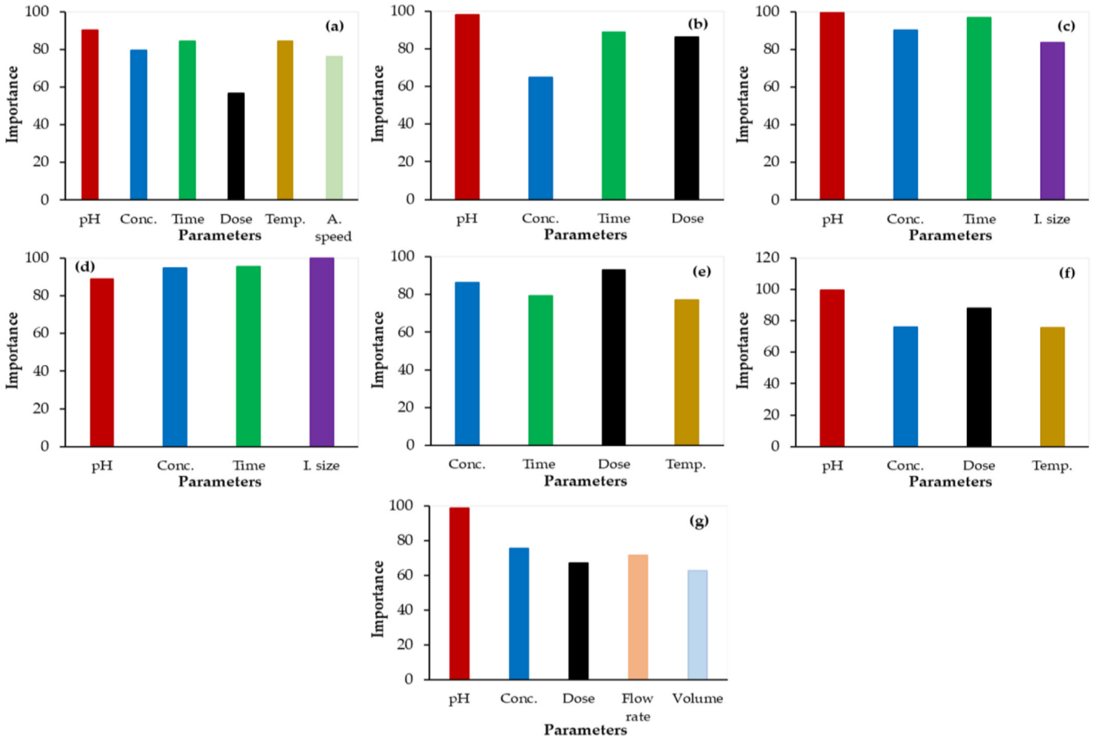

Figure 6 - Significance of the experimental parameters on the adsorption efficiency: (a) dataset 1, (b) dataset 2, (c) dataset 3, (d) dataset 4, (e) dataset 5, (f) dataset 6, and (g) dataset 7 [24].

CONCLUSION

Overall, this comprehensive review has highlighted the crucial role of artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) in modeling pollutant removal from wastewater. The urgency of addressing water pollution, exacerbated by industrial and agricultural activities, necessitates the development of efficient and reliable methods for water treatment. Traditional methods often fall short due to their time-consuming nature and limited predictive capabilities. In contrast, ANNs and ANFIS offer sophisticated modeling techniques that enhance the accuracy and efficiency of pollutant removal processes.

Our examination of various studies demonstrates that these intelligent systems can effectively predict the removal efficiencies of a wide range of pollutants, including heavy metals and organic compounds. The application of these models not only optimizes treatment processes but also facilitates the scaling-up and operational adjustment of wastewater treatment plants. The integration of AI in water quality management thus holds significant promise for advancing sustainable environmental practices. The review underscores the superior performance of hybrid training methods in ANFIS models, particularly in comparison to traditional backpropagation algorithms. The successful application of ANFIS and

ANN models in predicting the adsorption efficiency of contaminants such as arsenic and 2,4-Dichlorophenoxyacetic acid (2,4-D) validates their potential in practical scenarios. Furthermore, statistical analyses indicate that ANFIS models generally provide better forecasting accuracy compared to other predictive models like response surface methodology (RSM). Future research should continue to refine these models, exploring the integration of additional parameters and enhancing their adaptability to various pollutants and treatment conditions. The development of more robust datasets and the application of advanced algorithms will further improve the predictive power and operational efficiency of AI-based water treatment models.

In conclusion, the deployment of ANNs and ANFIS in modeling pollutant removal represents a significant advancement in the field of environmental engineering. These models offer a promising approach to improving the management and treatment of wastewater, contributing to the broader goal of environmental sustainability and protection. The insights gained from this review provide a strong foundation for future innovations and applications of AI in water treatment processes.

Declaration by Authors

Acknowledgement: None

Source of Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest: The authors declare no conflict of interest.

REFERENCES

1. S.S. Ahluwalia, D. Goyal, Microbial and plant derived biomass for removal of heavy metals from wastewater, Bioresour. Technol. 98 (2007) 2243–2257. https://doi.org/10.1016/j.biortech.2005.12.006.
2. R. Amna, S.M. Alhassan, Exploring porous sulfur copolymers for efficient removal of heavy metal ions from wastewater: A computational study, J. Ind. Eng. Chem. (2024). https://doi.org/10.1016/j.jiec.2024.04.014.
3. J. Zou, Y. Han, S.-S. So, Overview of Artificial Neural Networks, in: 2008: pp. 14–22. https://doi.org/10.1007/978-1-60327-101-1_2.
4. P. Michailidis, I. Michailidis, S. Gkelios, E. Kosmatopoulos, Artificial Neural Network Applications for Energy Management in Buildings: Current Trends and Future Directions, Energies. 17 (2024) 570. https://doi.org/10.3390/en17030570.
5. S. Palani, S.-Y. Liong, P. Tkalich, An ANN application for water quality forecasting, Mar. Pollut. Bull. 56 (2008) 1586–1597. https://doi.org/10.1016/j.marpolbul.2008.05.021.
6. E. Neverov, A. Gorelkina, I. Korotkiy, R. Skhaplok, Influence of the Properties and Concentration of Pollutants in Wastewater on the Choice of Methods and Technologies of Industrial Water Treatment: A Systematic Review, Adv. Life Sci. 10 (2023) 341–349.
7. A.G. Krishnan, P. Krishnamoorthy Lakshmi, S. Chellappan, Artificial neural network modelling approach for the prediction of turbidity removal efficiency of PACl and Moringa Oleifera in water treatment plants, Model. Earth Syst. Environ. 9 (2023) 2893–2903. https://doi.org/10.1007/s40808-022-01651-9.
8. H.Y.H. Alnajjar, O. Üçüncü, Removal efficiency prediction model based on the artificial neural network for pollution prevention in wastewater treatment plants, Arab Gulf J. Sci. Res. 41 (2023) 610–626. https://doi.org/10.1108/AGJSR-07-2022-0129.
9. P.L. Narayana, A.K. Maurya, X.-S. Wang, M.R. Harsha, O. Srikanth, A.A. Alnuaim, W.A. Hatamleh, A.A. Hatamleh, K.K. Cho, U.M.R. Paturi, N.S. Reddy, Artificial neural networks modeling for lead removal from aqueous solutions using iron oxide nanocomposites from bio-waste mass, Environ. Res. 199 (2021) 111370. https://doi.org/10.1016/j.envres.2021.111370.
10. D. Andina, A. Vega-Corona, J.I. Seijas, J. Torres-Garcìa, Neural Networks Historical Review, in: Comput. Intell., Springer US, Boston, MA, n.d.: pp. 39–65. https://doi.org/10.1007/0-387-37452-3_2.

11. L. Alzubaidi, J. Zhang, A.J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M.A. Fadhel, M. Al-Amidie, L. Farhan, Review of deep learning: concepts, CNN architectures, challenges, applications, future directions, J. Big Data. 8 (2021) 53. https://doi.org/10.1186/s40537-021-00444-8.
12. I.H. Sarker, Machine Learning: Algorithms, Real-World Applications and Research Directions, SN Comput. Sci. 2 (2021) 160. https://doi.org/10.1007/s42979-021-00592-x.
13. C. Lv, Y. Xing, J. Zhang, X. Na, Y. Li, T. Liu, D. Cao, F.-Y. Wang, Levenberg–Marquardt Backpropagation Training of Multilayer Neural Networks for State Estimation of a Safety-Critical Cyber-Physical System, IEEE Trans. Ind. Informatics. 14 (2018) 3436–3446. https://doi.org/10.1109/TII.2017.2777460.
14. S. Fatimah, Wiharto, Artificial neural network for modelling the removal of pollutants: A review, Eng. Appl. Sci. Res. 47 (2020) 339–347. https://doi.org/10.14456/easr.2020.36.
15. M.S. Nasr, M.A.E. Moustafa, H.A.E. Seif, G. El Kobrosy, Application of Artificial Neural Network (ANN) for the prediction of EL-AGAMY wastewater treatment plant performance-EGYPT, Alexandria Eng. J. 51 (2012) 37–43. https://doi.org/10.1016/j.aej.2012.07.005.
16. B. Rezai, E. Allahkarami, Application of Neural Networks in Wastewater Degradation Process for the Prediction of Removal Efficiency of Pollutants, in: Soft Comput. Tech. Solid Waste Wastewater Manag., Elsevier, 2021: pp. 75–93. https://doi.org/10.1016/B978-0-12-824463-0.00008-2.
17. A. Reynaldi, S. Lukas, H. Margaretha, Backpropagation and Levenberg-Marquardt Algorithm for Training Finite Element Neural Network, in: 2012 Sixth UKSim/AMSS Eur. Symp. Comput. Model. Simul., IEEE, 2012: pp. 89–94. https://doi.org/10.1109/EMS.2012.56.
18. M. Kayri, Predictive Abilities of Bayesian Regularization and Levenberg–Marquardt Algorithms in Artificial Neural Networks: A Comparative Empirical Study on Social Data, Math. Comput. Appl. 21 (2016) 20. https://doi.org/10.3390/mca21020020.
19. S. Porhemmat, M. Ghaedi, A.R. Rezvani, M.H.A. Azqhandi, A.A. Bazrafshan, Nanocomposites: Synthesis, characterization and its application to removal azo dyes using ultrasonic assisted method: Modeling and optimization, Ultrason. Sonochem. 38 (2017) 530–543. https://doi.org/10.1016/j.ultsonch.2017.03.053.
20. S.A. Bhat, G. Cui, W. Li, Y. Wei, F. Li, S. Kumar, F. Ameen, Challenges and opportunities associated with wastewater treatment systems, in: Curr. Dev. Biotechnol. Bioeng., Elsevier, 2021: pp. 259–283. https://doi.org/10.1016/B978-0-12-821009-3.00008-7.
21. H. ALNAJJAR, O. ÜÇÜNCÜ, Enhance modelling predicting for pollution removal in wastewater treatment plants by using an adaptive neuro-fuzzy inference system, Environ. Res. Technol. 5 (2022) 213–226. https://doi.org/10.35208/ert.1106463.
22. M. Mahshidnia, A. Jafarian, Forecasting Wastewater Treatment Results with an ANFIS Intelligent System, Eng. Technol. Appl. Sci. Res. 6 (2016) 1175–1181. https://doi.org/10.48084/etasr.745.
23. S. H, R. Bhat M, R. Selvaraj, Removal of an agricultural herbicide (2,4-Dichlorophenoxyacetic acid) using magnetic nanocomposite: A combined experimental and modeling studies, Environ. Res. 238 (2023) 117124. https://doi.org/10.1016/j.envres.2023.117124.
24. M. Al-Yaari, T.H.H. Aldhyani, S. Rushd, Prediction of Arsenic Removal from Contaminated Water Using Artificial Neural Network Model, Appl. Sci. 12 (2022) 999. https://doi.org/10.3390/app12030999.

How to cite this article: Tran Nhat Minh, Nguyen Thanh Truyen, Dinh Thi Hong Loan. Artificial neural networks for modeling pollutant removal in wastewater treatment: a review. *Galore International Journal of Applied Sciences & Humanities*. 2024; 8(2): 88-98. *DOI: https://doi.org/10.52403/gijash.20240211*

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