Estimation of Biochemical Oxygen Demand with Artificial Neural Networks Optimized by Hybrid BBO-GA: Application at Bouira Wastewater Treatment Plants

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Abstract

Addressing the global water crisis requires efficient wastewater treatment and reuse, where accurate estimation of Biochemical Oxygen Demand (BOD) is a key factor. Traditionally, BOD is measured as BOD_5, requiring a five-day incubation period. This long delay means that calculations of purification parameters rely on outdated values from the previous five days, often leading to imprecise monitoring and control.

Previous studies using Artificial Neural Networks (ANNs) for BOD estimation have mainly focused on optimizing the weights and biases, while the number of hidden layers and neurons within each layer is usually determined experimentally—a process that is both time-consuming and often imprecise. In this work, we propose a hybrid artificial intelligence (AI) approach that addresses this limitation. The optimal ANN architecture is automatically determined using a Genetic Algorithm (GA), a heuristic method inspired by natural selection, while the weights and biases are further fine-tuned using Biogeography-Based Optimization (BBO). This dual optimization strategy significantly improves model robustness and accuracy.
By modeling the relationship between BOD and easily measurable parameters such as Chemical Oxygen Demand (COD) and Total Suspended Solids (TSS), and applying it to data from the Bouira wastewater treatment plant, our method enables rapid and precise same-day BOD prediction. This AI-driven approach eliminates the five-day lag of conventional methods, enhances the accuracy of purification parameter calculations, and supports more effective real-time monitoring for sustainable water management.

Keywords

ANN, GA, BBO, BOD, Total Suspended Solids, Chemical Oxygen Demand.

1. Introduction

The overexploitation of freshwater resources over time has led to declining river flows, falling water tables, and the degradation of wetlands across the globe. This depletion has caused widespread soil salinization, desertification, and other forms of environmental degradation **(Ali et al., 2024)**. Furthermore, the daily struggle to access sufficient and clean water has become a significant challenge, with severe consequences for public health, hygiene, food security, and economic stability in numerous regions.

Water scarcity has emerged as one of the most critical challenges of the 21st century, affecting millions of people worldwide and having profound impacts on natural ecosystems. As global population growth intensifies the pressure on freshwater resources, climate change exacerbates the situation by causing unpredictable weather patterns, including more frequent and severe droughts **(Shemer et al., 2023)**. This growing concern is not merely an environmental issue but also a major obstacle to economic and social development.

In this context, wastewater reuse presents a viable solution to the global water shortage. It plays a crucial role in ensuring the sustainability of water resources, mitigating the effects of climate change, and meeting the increasing water demands of communities, agriculture, and industry while safeguarding the environment and public health **(Silva, 2023)**. For wastewater reuse to be effective, it must be supported by robust treatment systems, advanced infrastructure, and sophisticated technologies. Moreover, effective management, as well as appropriate policies and regulations, are essential for the safe, sustainable, and socially acceptable use of recycled water.

Accurate estimation of Biochemical Oxygen Demand (BOD) is vital for assessing wastewater quality and managing treatment processes. BOD measures the oxygen required to decompose organic matter in wastewater and serves as a key indicator of water pollution. However, traditional BOD estimation methods are time-consuming and labor-intensive, limiting their utility in real-time monitoring and control **(Górski et al., 2012)**.

Machine learning techniques offer promising solutions to these challenges. Artificial Neural Networks (ANNs), in particular, are well-suited for handling time-series data such as wastewater quality parameters. ANNs can capture temporal dependencies and non-linear relationships between variables, making them ideal for modeling complex environmental systems **(Elmotawakkil et al., 2025)**.

However, training ANNs presents challenges due to the need to optimize numerous hyperparameters. Biogeography-Based Optimization (BBO), a nature-inspired algorithm, can effectively tune the weights and biases of the ANN, thereby enhancing its performance **(Xin et al., 2024)**. Additionally, Genetic Algorithms (GA) can be employed to optimize the number of hidden layers and the number of neurons in each layer, further improving the model's accuracy.

This study introduces a novel approach to estimating BOD from Chemical Oxygen Demand (COD) and Total Suspended Solids (TSS) using feedforward Neural Network (ANN) optimized by BBO and GA. The proposed model is evaluated using an extensive dataset from the Bouïra Wastewater Treatment Plant in Algeria. The results demonstrate the effectiveness of this approach when compared to existing methods.

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2. Materials and Methods

2.1. Experimental Site Description

The wastewater treatment plant (STEP) in Bouira, situated upstream of the Tilesdit dam on the Oued Hous river (Figure 1), is a new facility with a nominal capacity of 129,200 equivalent inhabitants, collecting urban and rainwater from the city. Its primary purpose is to protect the Tilesdit dam, which serves as the main source for irrigation and drinking water supply for Bouira. Operated by the National Sanitation Office (ONA) since June 1, 2013, the plant covers a total area of 10 hectares, with 6 hectares covered, and employs 34 people.

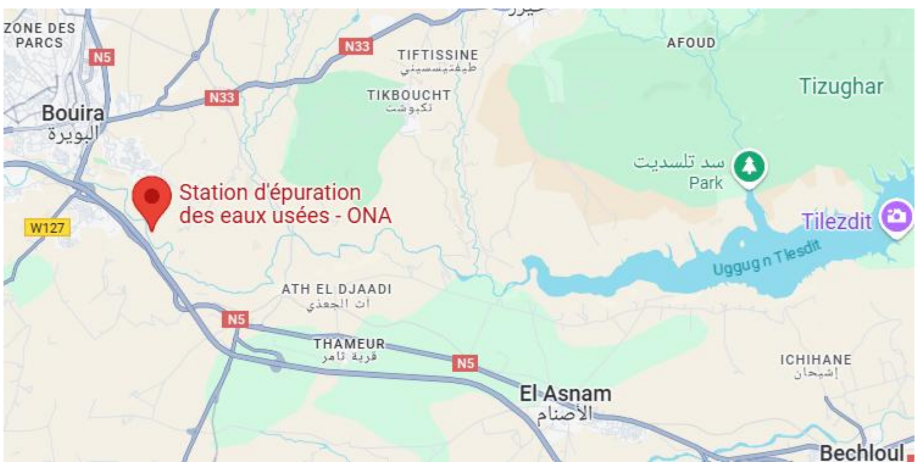

Figure 1: Localization of the wastewater treatment plant of Bouira.

2.1.1. Purification process

The treatment process at the Bouira STEP begins with the collection and pumping of wastewater to the plant. It then undergoes a mechanical pre-treatment stage, starting with a manual coarse screening to remove large impurities (>50mm), followed by automatic fine screening for smaller impurities (>8mm). This is succeeded by two grit and oil removal lines where sand is eliminated by decantation and oils by flotation using pressurized air.

Following pre-treatment, the water is directed to a distributor where it mixes with return sludge in a contact zone to form activated sludge, which then flows into the biological basins. Each biological basin consists of an anoxic zone for denitrification (reduction of nitrates to nitrogen gas) and an aerobic zone for the biological oxidation of carbonaceous and nitrogenous pollution (nitrification), with potential biological phosphorus removal facilitated by a syncopated aeration system. These basins are aerated by horizontal surface aerators (mammoth rotors) and agitated by submersible agitators.

After biological degradation, the water moves to two clarifiers for the separation of purified water and sludge through simple decantation. The purified water is then discharged from the clarifiers to disinfection baffles (currently inactive) before being released into the Oued Hous. A portion of the sludge from the clarifiers is recycled back to the biological basins, while the excess sludge is sent to a thickener for thickening, then to an aerobic stabilizer, and finally to mechanical dewatering using two belt presses with the addition of cationic polymer, or it can be dried naturally in drying beds.The entirety of the Bouira wastewater treatment plant (STEP) is depicted in Figure 2.

Figure 2: Aerial view of the wastewater treatment plant of Bouira.

2.1.2. Efficiency indicators

In the context of this study, evaluating the efficiency of wastewater treatment processes is paramount. To achieve this, three key parameters were utilized as indicators of water quality and pollution levels, drawing upon standard definitions and methodologies relevant to wastewater analysis:

Biochemical Oxygen Demand (BOD5): BOD5 measures the amount of oxygen required by microorganisms to break down biodegradable organic matter in wastewater over a five-day period at 20°C. It reflects the level of biologically degradable material present and is expressed in milligrams of oxygen per liter (mg O_2/L). BOD5 is a critical indicator because a reduction in its levels after treatment indicates decreased organic pollution and improved water quality. However, it only accounts for biodegradable organic matter and not non-biodegradable substances **(Lacalamita et al., 2024)**.

Chemical Oxygen Demand (COD): COD quantifies the total oxygen demand needed to oxidize all organic matter in wastewater, including both biodegradable and non-biodegradable substances. Like BOD5, COD is expressed in mg O_2/L and serves as a measure of the organic load in wastewater. Reducing COD is crucial in treatment processes to enhance water quality. Techniques such as biological treatments (e.g., activated sludge) and physico-chemical methods (e.g., chemical oxidation) are employed to lower COD by removing organic contaminants **(Lacalamita et al., 2024)**.

Total Suspended Solids (TSS): TSS represents solid and colloidal particles suspended in wastewater, which can include sediments, organic matter, and other debris from various sources such as domestic wastewater, urban runoff, and industrial activities. These particles can carry harmful contaminants like heavy metals, bacteria, and viruses, posing risks to the environment and human health. TSS also impacts water clarity and can hinder sunlight penetration, affecting aquatic ecosystems. Treatment processes like filtration, settling, and biological methods are used to remove these particles, thus improving water clarity, reducing the risk of equipment clogging, and enhancing the efficiency of subsequent treatment stages **(Soto et al., 2025)**. The concentration of SS is typically expressed in milligrams per liter (mg/L).

Collectively, these parameters (BOD5, COD, and TSS) are essential indicators of water quality and pollution levels. They provide a comprehensive assessment of wastewater quality and the effectiveness of treatment processes in reducing pollution and improving environmental outcomes.

2.2. Literature Review

2.2.1. ANNS for BOD prediction

Artificial Neural Networks (ANNs) are composed of artificial neurons, which mimic the behavior of biological neurons. Neurons receive inputs, multiply them by weights, add a bias, and pass the result through an activation function to produce an output. The weights and bias are learned through a process called backpropagation, which involves forward propagation of input data through the network to generate an output, followed by error calculation and backward propagation to update weights and biases. To prevent overfitting, techniques like regularization can be applied, while underfitting can be addressed by careful tuning of hyperparameters like the number of hidden layers and neurons within each layer which can vary depending on the complexity of the problem and the desired level of accuracy.

The versatility of ANNs has led to their widespread adoption in engineering, including civil, mechanical, electrical, and aerospace engineering. They are used for tasks such as structural health monitoring, traffic prediction, design optimization, power system optimization, and environmental modeling. ANNs' ability to learn from data and model complex relationships makes them particularly valuable for addressing intricate environmental challenges.

A comprehensive overview of the application of neurocomputing models in hydrological and hydraulic sciences reveals a growing trend towards their utilization in addressing complex water-related challenges. **(Nasr at al., 2017)** utilized artificial intelligence to model cadmium biosorption using rice straw. **(Zounemat-Kermani et al., 2019)** applied multivariate NARX neural networks to predict gaseous emissions in wastewater treatment. **(Chen et al., 2020)** explore how reinforcement learning can be used to make real-time decisions in water distribution systems, improving efficiency and sustainability. **(Kumar et al., 2021)** provide insights into how RNNs can effectively model temporal dependencies in water quality data, leading to better management practices. **(Kheimi et al., 2022)** employed machine learning models to simulate heavy metals in wastewater treatment plants. **(Viet et al., 2023)** developed a machine learning-based real-time prediction system for micropollutants in forward osmosis membrane wastewater treatment.

Within the realm of wastewater treatment, accurately predicting BOD is paramount for effective process control and effluent quality management. Traditional methods for BOD determination are time-consuming and labor-intensive, hindering real-time applications. To address these limitations and enhance operational efficiency, researchers have increasingly explored the potential of neurocomputing techniques. Early studies by **(Noori et al., 2013; Qiao et al., 2014; Heddam et al., 2016; Zounemat-Kermani et al., 2022)** laid the groundwork, demonstrating the feasibility of applying neural networks to BOD prediction. Subsequently, (**Yu et al., 2019; Mekaoussi et al., 2023)** advanced the field through the development of optimized models and hybrid approaches, respectively. These studies collectively underscore the potential of neurocomputing to significantly improve BOD prediction accuracy and inform wastewater treatment strategies.

This study leverages the capabilities of Artificial Neural Networks (ANN) to predict BOD based on a robust dataset spanning one year from the Wastewater Treatment Plant (WTP) of Bouira, Algeria. The extensive historical data provides a solid foundation for training the ANN model, enabling it to accurately capture the complex relationships between TSS, COD, and BOD. By overcoming the limitations of traditional BOD5 measurement methods, this research aims to contribute to the development of more efficient and reliable wastewater treatment processes.

2.2.2. Optimization techniques

Biogeography-Based Optimization (BBO) and Genetic Algorithm (GA) are two metaheuristic optimization algorithms inspired by natural phenomena. They are often used to solve complex optimization problems, especially when traditional methods fail to find satisfactory solutions **(Simon et al., 2011)**.

Biogeography-Based Optimization (BBO) is inspired by the geographical distribution of species and their migration patterns **(Simon, 2008).** In BBO, potential solutions are represented as habitats, and new information is introduced to these habitats through immigration. Information may also leave a habitat through emigration. The best solutions are preserved through elitism, while mutation introduces random changes to the solutions. The algorithm iteratively improves solutions by simulating the migration of individuals between habitats, with the rate of migration depending on the habitat's suitability. This process continues until a satisfactory solution is found.

However, Genetic Algorithm (GA) is inspired by the process of natural selection in biology **(Naaman et al., 2025)**. In GA, potential solutions are represented as chromosomes, which are composed of genes. A group of chromosomes forms a population. The fitness of a chromosome measures how well it solves the problem. The algorithm iteratively improves solutions by selecting the fittest individuals, combining their genetic material through crossover, and introducing random mutations to explore new solutions. This process continues until a satisfactory solution is found.

Both BBO and GA are effective optimization algorithms with their own strengths and weaknesses. BBO is often praised for its simplicity and robustness, while GA is known for its versatility and ability to explore a wide range of solution spaces **(Amamra et al., 2023)**. The choice between BBO and GA often depends on the specific characteristics of the optimization problem.

2.3. Methodology

Data Acquisition and Preparation: A dataset was compiled from the Bouira Wastewater Treatment Plant, consisting of daily measurements of chemical oxygen demand (COD), total suspended solids (TSS), and biochemical oxygen demand (BOD). To train and evaluate the model effectively, the dataset was divided into three subsets: a training set (70%), a validation set (20%), and a testing set (10%).

Artificial Neural Network (ANN) Model Development: An ANN model was constructed to predict BOD values based on COD and TSS measurements. The optimal number of hidden layers and neurons within each layer were determined using a genetic algorithm (GA), a heuristic optimization technique inspired by natural selection. The weights and biases of the ANN were further fine-tuned using biogeography-based optimization (BBO), a metaheuristic algorithm that simulates the migration of species between habitats.

Model Training and Evaluation: The ANN model was trained using the training dataset, with the goal of minimizing the mean squared error (MSE) between the predicted and actual BOD values. This objective function guides the optimization process to find the best possible parameter values for the model.

Once trained, the model's performance was evaluated on the unseen testing dataset. Two metrics were used to assess the model's accuracy: MSE and correlation coefficient. MSE measures the average squared difference between predicted and actual values, while the correlation coefficient indicates the strength and direction of the linear relationship between predicted and actual values.

Figure 3 present a flowchart illustrating the proposed hybrid GA-BBO-ANN model. The model iteratively updates the neural network's architecture (using GA) and weights/biases (using BBO) to optimize BOD prediction. The process continues until both GA and BBO stop criteria are met.

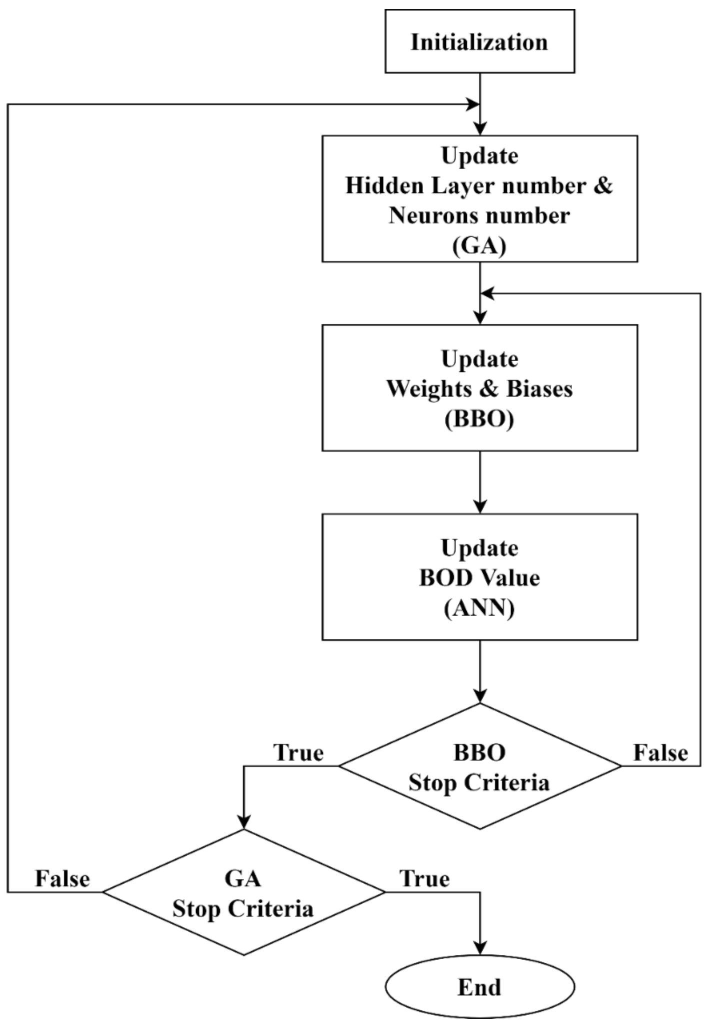

Figure 3: Hybrid GA-BBO-ANN Model for BOD Prediction (Source: Authors)

3. Results and Discussion

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Present your findings clearly. Include tables, figures, and statistical analyses where relevant.

Figure 4 outlines the neural network architecture, which comprises an input layer with 2 neurons, likely corresponding to the input features COD and TSS. Following this, there are 4 hidden layers of varying neuron counts, demonstrating the network's capacity for complex pattern recognition. Finally, the output layer consists of a single neuron, suggesting the network's intended purpose of predicting a single value, presumably the BOD.

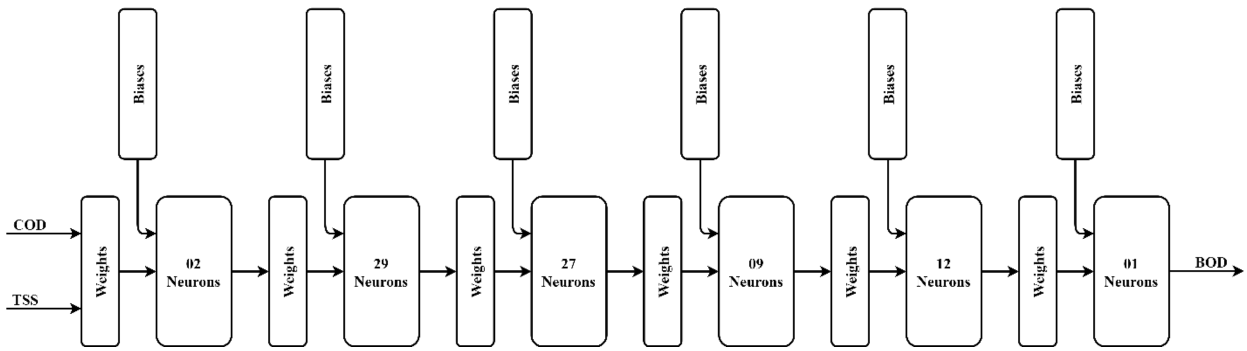

Figure 4: Neural Network Architecture for BOD Prediction.

This architecture, featuring multiple hidden layers and varying neuron counts, empowers it to learn complex patterns from the input data and capture nonlinear relationships between the input and output. However, this complexity also increases the risk of overfitting, especially when training data is limited. To address this concern, we implemented a consistent monitoring strategy. By systematically observing the validation loss throughout the training process, we were able to identify early signs of overfitting.

Figure 5 illustrates the ANN's training progress, visualizing how the Mean Squared Error (MSE) changes during training, validation, and testing. A decreasing training MSE signifies effective learning from the training data. Conversely, a rising validation MSE while the training MSE continues to decline suggests overfitting. The testing MSE assesses the model's generalization ability on new data.

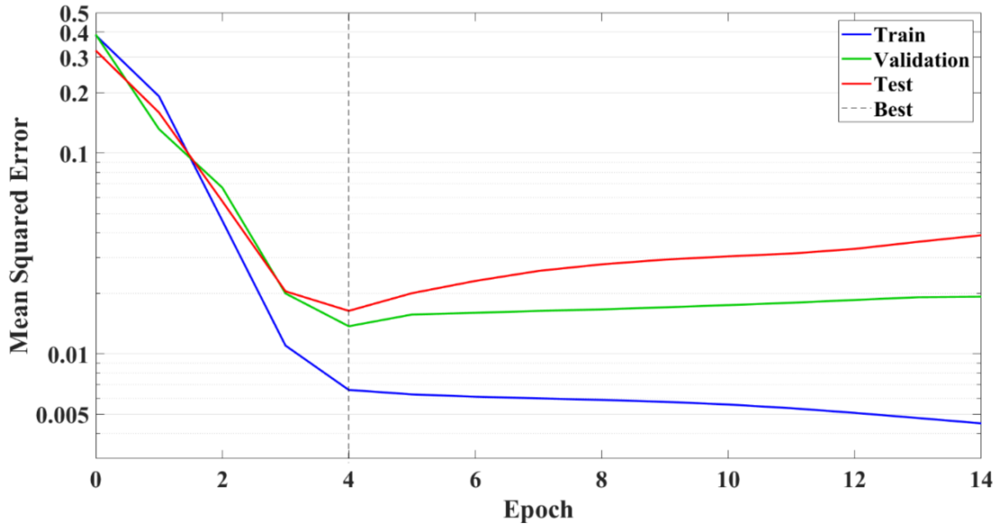

Figure 5: ANN Training Performance.

In this Figure, the validation Mean Squared Error (MSE) decreases until the fourth epoch, after which it begins to increase, signaling the onset of overfitting. The fourth epoch is considered the optimal point to stop training for the best model generalization and optimal performance on unseen data.

Figure 6 illustrates the neural network's performance, showcasing four scatter plots representing the relationship between predicted and target values, with a black dashed line representing perfect predictions.

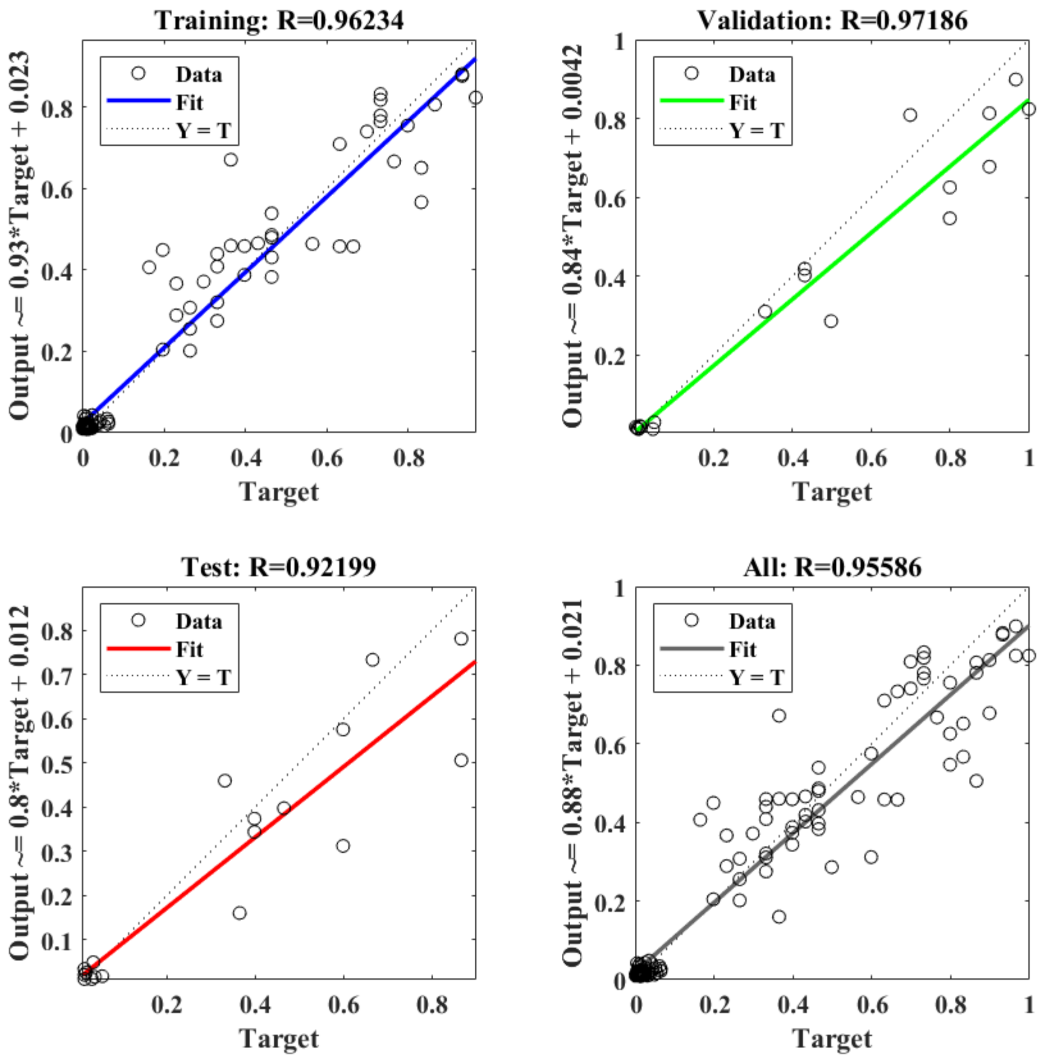

Figure 6: Scatter plots illustrating neural network performance (Source: Authors).

R-squared values which represent the correlation coefficients, reveal a strong model fit, with training, validation, test, and overall R^2 values of 0.96234, 0.97186, 0.92199, and 0.95586, respectively. The scatter plots demonstrate a clear linear correlation, as evidenced by the output equations provided, with some variability observed in the test set. While slight overfitting is suggested, the model exhibits strong generalization capabilities.

Table 1 provides a clear comparison of the effectiveness of different methods used by various researchers, with the R^2 value serving as the key metric for model performance.

Table 1. Comparison of R^2 Values for Predictive Models in Previous Studies (2017-2023).

Author	Year	Method	R^2
Mekaoussi et al.	2023	ELM_Bat	0.885
		RFR	0.795
		GPR	0.795
		MLPNN	0.770
		RVFL	0.765
		MLR	0.709
Aghdam et al.	2023	GEP	0.865
		RFR	0.841
		KNN	0.822
		MLR	0.818
		MLPNN	0.809
		GB	0.799
		RT	0.752
Qambar et al.	2022	RFR	0.920
		GB	0.400
Golabi et al.	2020	RFR	0.872
		M5Tree	0.751
Solgi et al.	2017	SVR	0.918
		ANFIS	0.910

Source: Authors.

This review of existing literature reveals a diverse range of predictive methods for BOD prediction. While various approaches have shown varying degrees of success, the ELM_Bat method, as highlighted by **(Mekaoussi et al. 2023)**, consistently demonstrated superior predictive performance, achieving an R^2 value of 0.885.

Other notable methods include RFR, GPR, and MLPNN, which have exhibited moderate effectiveness across multiple studies. Notable examples include **(Aghdam et al. 2023; Qambar et al. 2022)**, who reported promising results with GEP and RFR, respectively.

The current study significantly advances the field by achieving an exceptionally high R^2 of 0.97186 during validation, surpassing all previously reported values. Even when evaluated on the test set, the model maintains a robust predictive performance, with an R^2 of 0.95586.This minimal discrepancy between validation and test R^2 underscores the model's exceptional generalization capabilities, demonstrating its ability to consistently maintain high accuracy across different datasets.

4. Conclusion

This study introduces a novel approach for estimating Biochemical Oxygen Demand (BOD) from Chemical Oxygen Demand (COD) and Total Suspended Solids (TSS) using Artificial Neural Networks (ANNs) optimized by Biogeography-Based Optimization (BBO) and Genetic Algorithm (GA). The proposed model, applied to data from the

Bouïra Wastewater Treatment Plant in Algeria, demonstrates superior performance compared to existing methods, achieving an R^2 value of 0.97186 for validation and 0.95586 for the test dataset. These results highlight the model's high accuracy and robust generalization capabilities, significantly advancing the field of wastewater treatment and offering a promising tool for real-time monitoring and control. The findings underscore the potential of ANNs, particularly when optimized with advanced algorithms like BBO and GA, to enhance wastewater treatment processes and contribute to sustainable water management.

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