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Wastewater Efficiency Prediction using Artificial Neural Networks

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Abstract

The purpose of this article is to use ANN models to forecast how well industries dispose of their waste water (IDWW). It's useful for anything from evaluating potential design and modelling errors to managing day-to-day operations at a IDWW. This work utilizes data on chemical oxygen demand (COD), biochemical oxygen demand (BOD), total suspended solid (TSS), pH, temperature (T), and other factors to develop a predictive model of the system's performance. Techniques like artificial neural networks (ANNs) may be used to evaluate environmental balance stability and cut down on operational costs. The model's viability as a soft sensor for control and management systems for IDWWs was determined by comparing observed and forecasted output variables using statistical analysis measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient (R). When it comes to evaluating data, neural network analysis often use the PYTHON programming language, however ANN models provide an alternative, simpler method.

Keywords

Artificial Neural Network (ANN), Industry dispose Waste Water, Modeling, Python, Statistical Analysis.*

INTRODUCTION

In each aquatic system, water quality is crucial since it reflects the level of water pollution and affects the development of aquatic creatures. Predicting changes in water quality has critical functions in environmental monitoring, ecosystem management, and human health, among other areas [1]. The goal of wastewater treatment is to restore recycled water to the environment in a more sustainable form. Thus, it is essential for industry operators and managers to have a firm grasp of the mechanics of effective industry performance [2].

Wastewater is processed at IDWW before being released back into the environment, lakes, or streams. Primary treatment, secondary treatment, and tertiary treatment make up the conventional wastewater treatment procedure. Solids that may float or sink must be separated out during basic treatment. Biodegradable organic materials and dissolved solids are mostly removed during secondary treatment. Organic materials in trash that can be decomposed into carbon dioxide, water, methane, or simple organic molecules by micro-organisms and other living things via composting, aerobicdigestion, anaerobic digestion, or similar processes is removed during tertiary treatment [3]. There are extremely non-linear and dynamic physical, biological, and chemical processes at play [4]. Water is essential to many industrial processes. Water waste is a byproduct of almost every industrial sector. Minimizing such production or reusing treated wastewater inside the industrial process has been more popular in recent years.

Several of these sectors have succeeded in revamping their production methods to eliminate or drastically cut down on pollution. The production of batteries, chemicals, electric power, food, iron and steel, metal working, mines and quarries, nuclear power, petroleum refining and petrochemicals, pharmaceuticals, pulp and paper, smelters, textile mills, industrial oil contamination, water treatment, and wood preservatives are all examples of industries that generate wastewater [5]. Brine treatment, solids removal (such as chemical precipitation, filtering), oils and grease removal, biodegradable organics removal, other organics removal, acids and alkalis removal, and hazardous compounds removal are all examples of treatment methods [7].

Artificial Neural Network (ANN) will be employed since it is a highly precise, capable mathematical tool with potential engineering applications for forecasting the success of an industry based on historical observations of that sector's performance [9]. They are used to big IDWWs [10], where ANNs are used for control of dynamic systems with varied degrees of precision and amount of input data. Operators will be able to predict industrial effluent based on the performance of an ANN trained on 20 years of dynamic data. This research shown that the IDWWs may be captured by ANNs using their operational features with a high degree of accuracy [6]. One of the most widely used forms of machine learning, which itself is a subfield of AI, is the use of neural networks. It displays the total number of papers on membrane modelling and establishes a correlation between input and output variables. Some of the variety of MLP-ANN may be accounted for by switching up the model's parameters and training procedures, as shown by the Radial Basis Function Neural Network (RBFNN), Recurrent Neural Network (RNN), Elman Neural Network (ENN), and Deep Neural Network (DNN) [3]. BackPropagation (BP), a feed forward neural network also known as multilayer perceptron (MLP), [8] is the most used ANN.

INDUSTRIES FOR POLLUTION AND WASTEWATER TREATMENT

Wastewater is the unclean, grey water that is discharged from hospitals, businesses, homes, and other locations. It contains nutrients, bacteria, dissolved and suspended particles, and organic and inorganic pollutants.

1. Organic impurities: human faces, animal waste, oil, urea (urinary waste), pesticides, herbicides, leftover fruit, etc.
2. Inorganic contaminants, such as metals, phosphate, and nitrate.
3. Phosphorous and nitrogen are nutrients.
4. Bacteria, such as salmonella paratyphi, which causes typhoid, and cholera, which causes cholera.
5. Other microorganisms, such as the dysentery-causing protozoa.

Types of Waste Water

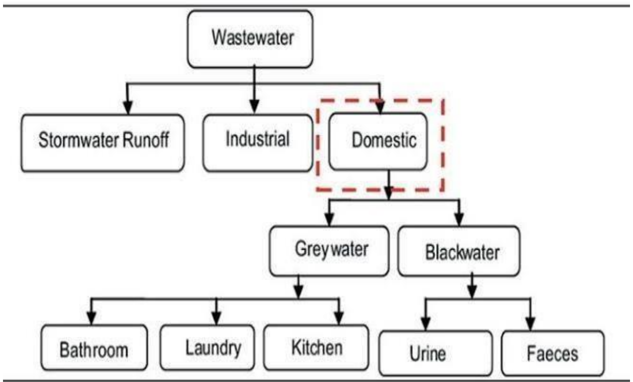

Figure 1. Wastewater types

What Makes Up Wastewater

To put it simply, waste water is any water whose quality has been diminished due to human activity.

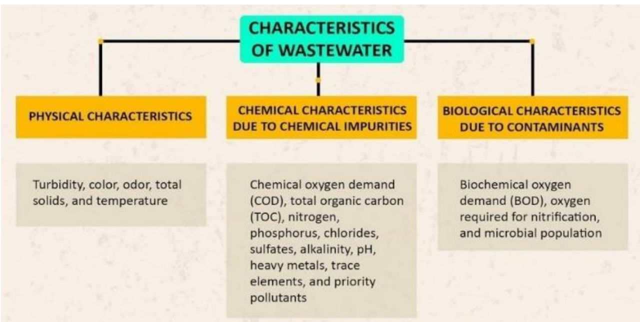

Figure 2. Characteristics of wastewater

In the wastewater treatment industry, specialised procedures are used to remove organic matter and other impurities from wastewater. The goal of wastewater treatment is to produce water that is suitable for reuse in the environment without posing any health risks to the local population or ecology.

There are four basic types of wastewater treatment systems:

1) Sewage Treatment Industrys (STPs)
2) Effluent Treatment Industrys (ETPs)
3) Activated Sludge Industrys (ASPs)
4) Common or Combined Effluent Treatment Industrys (CETPs)

EXISTING TREATMENT TECHNIQUES

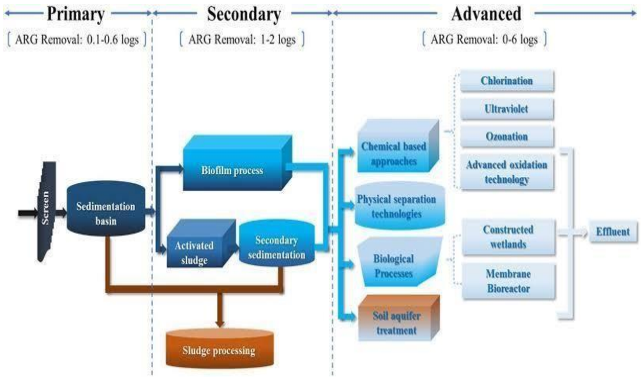

Figure 3. ARG Removal process visualized in stagewise

Artificial Neural Networks (ANNs)

Fundamentals of ANN: Neural Networks are another name for Artificial Neural Networks. Network size refers to the total number of connections between neurons. They've made real efforts to collaborate on data exchange. One definition of an ANN as follows:

- A non-linear computing model that takes its cues from the brain (specifically, biological neurons) and, like humans, learns through experience. By analysing training data, ANNs are able to perform a variety of tasks, including classification, prediction, decision making, visualisation, and more. The artificial neurons (or processing elements) of an ANN are many in number, and they work in parallel. Each neuron has its own unique set of connections with other neurons, and the input signal is encoded in the weights associated with those links. While trying to solve an issue, weight is the most helpful piece of information for neurons to have, since it may either stimulate or block the impulses being sent. Each neuron contains a single output, one input, and a set of weighted inputs (synapses) that together create the activation function.
- The benefits of ANN over more traditional models make this a reality. The following are examples of these benefits:
- Need less specialised statistical training for model construction.
- Ability to capture nonlinear relationships between predictors and outcomes as well as interactions between predictors.

- Many distinct training algorithms are available for use.
- Although ANN modelling with fresh data has many benefits, it also has significant restrictions.
- Model parameters are difficult to understand clinically (black boxes).
- It is challenging to share an existing ANN model.
- Overfitting is likely owing to the complicated model structure.
- It is challenging to determine confidence intervals for the expected hazards.
- The model is empirically developed. Guidelines for selecting optimal network architectures and training techniques are few.

ANN MODEL

In the above diagram, the letters a1, a2,…., an represent the network's different input (independent variables). A synapse weight, also known as a connection weight, is applied to each of these inputs.

Weight

Weight w1j, w2j,..., wnj demonstrates the quality of the link between pairs of nodes (neurons). Adding a weight reduces the significance of the input value.

Nodes/Neurons

It's the building block of every neural network. A set of inputs and a bias value are given. Extra information sent into neurons; always equal to 1; must have its own connection weight. The value of the bias fed into an activation function when all other inputs are zero. Multilayer Artificial Neural Network: Artificial neural networks (ANNs) are composed of artificial neurons (or processing elements) and are structured in three stacked layers.

1) Input Layer (Single)
2) Hidden Layer (One or more)
3) Output Layer (Single)

Input Layer:

Layers 1 and 2 of a neural network. The neurons in this layer take in data from the output world and pass it on to the layer below (i.e. Hidden layer). It does not modify the input data in any way, and it does not have any related weights or biases.

Hidden Layer

These neurons are located in the intermediate layer between the input and output. The hidden layer's responsibility is to modify the input such that the output unit may make use of it. Adding additional neurons to the system's hidden layers boosts its computational and processing capability, but makes training two systems more difficult.

Output Layer

It's the last layer in the neural network and it takes input from the last hidden layer, allowing us to generate as many or as few values (outputs) as we'd like within a certain tolerance.

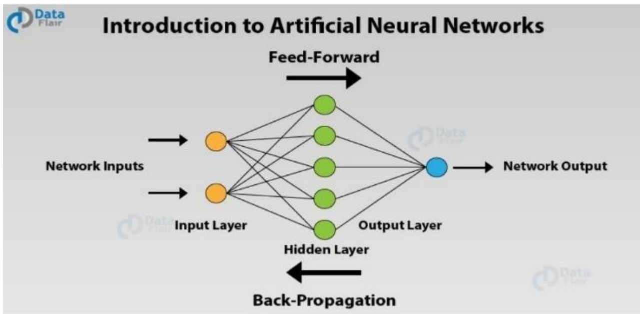

Figure 4. ANN Overview

ANN ALGORITHM

The external environment provides ANN with input in the form of patterns and images in vector form. Activation functions in ANNs are often used to transform the input signal at a node into the desired output signal. The network's subsequent layer takes this signal as input.

Point to the required amount the cutoff point has been determined.

The total is then sent via an activation function for these. To obtain an output in the [0,1], [-1,1] range, the activation function is employed to set the transfer function.

Figure 1 depicts a basic perceptron network, with a single hidden layer, and the threshold value (bj) or summing function is,

$$u_j = \sum_{i=1}^{n} (w_{ij} + a_i) + b_j$$

The net input to a node is used to calculate the node's output. Transfer functions or activation functions describe the process being performed.

Hyperbolic Tangent Transfer Function

It is similar to sigmoid function but better in performance. The advantage is that the negative input will be mapped strongly negative and the zero input will be mapped near zero in the tanh graph. The function range between [-1,1]. It is symmetric around the origin.

$$f(x) = \tan h = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad -1 \le f(x) \le 1$$

Sigmoid (Logistic) Activation Function

It is a very popular non-linear function. It operates on numbers in the range [0,1] to produce new ones.

Threshold Activation Function

The threshold-based activation function known as the binary step function. The Heaviside Function, for its other name.

$$f(x) = \begin{cases} x = 0, & x < 0 \\ x = 1, & x > 0 \end{cases}$$

Linear Transfer Function

$f(x) = x - \infty < f(x) < +\infty$

The neuron's output oj is calculated by applying one of these operations to the net input uj.

LOSS AND COST FUNCTION IN MACHINES

The performance of machine learning algorithms in modelling datasets is evaluated using loss function.

The loss function and machine learning algorithm aid our efforts. The loss function optimises its prediction error using a function like gradient descent. For a lone training instance, we have a loss function/error function. The overall loss during training is the cost function. Gradient descent and other optimisation strategies seek to keep an eye on the cost function.

Squared Error Loss

The squared error loss measures how much each training example deviates from the true value..

∴ L=(y-f(x))2or ∴ L=(y-y^)2

where y=Real Value and y=Analysis Error The associated cost function is the median squared error of these (MSE).

$$\therefore \text{MSE}= \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{n}$$

Where n is the number of observations

The average squared discrepancy between the model's predictions and the data's actual results is the mean square error metric. The smaller the MSE, the more accurate the forecasts.

Absolute Error Loss

Differences between expected and observed results during training are referred to as absolute error.

$$\therefore \text{L}=|\text{y-f(x)}| \text{ or } \therefore \text{L}=|\text{y-y\^}|$$

$$\therefore \text{MAE} = \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{n}$$

One of the most used optimisation algorithms for ML model training is gradient descent. In order to update the model's or parameter's weight, the optimises a search approach. Machine learning models are evaluated using a cost function for a set of input parameters (weights and biases). Finding a decent set of weights for our model that minimises the cost function is the goal of our learning problem (ANN). Therefore, gradient descent is a kind of optimization procedure for minimising prediction inaccuracy (cost function).

INSTRUCTIONAL MODELING AND NETWORK DEVELOPMENT

Parameter tuning is a primary focus of ANN research since achieving optimum network design is crucial for completing challenging jobs. In the neural network literature, several heuristic techniques for optimising training, choosing the right sized network, using the supervised learning paradigm, and estimating the amount of data needed to achieve a desired generalisation performance are presented. Even if all other Python NN toolbox parameters and the NN architecture are kept the same, the initial weight may have a significant effect on the trained NN's performance.

After a number of iterations of trial and error, the optimal network design was found to be one with a certain combination of learning rate, number of hidden layers, and number of neurons (fewer than 30 per each hidden layer). There are N iterations of this procedure, where N is the total number of nodes in the first hidden layer. A supervised learning back propagation approach is chosen for this research. This is done again and again with a different number of hidden nodes in layers two and three.

Network Properties

After the completion of the statistical analysis phase, the PYTHON-based neural network model was developed. The Network and Data Manager windows of PYTHON Toolbox provide access to functions for working with and exporting neural networks and data. The characteristics of the Network are as follows:

- COD, BOD, pH, and SS are all network inputs.
- COD, BOD, and IPH SS as network output
- Back-propagation and feed-forward networks.
- The LEARNGDM Adaptive Learning Function
- TRAINLM is the training function.
- The Levenberg-Marquardt (LM) training algorithm
- Measure of Statistical Error (MSE)
- The number of secret levels might be 1, 2, or 3.

RESULT AND DISCUSSION

Comparisons of BOD, COD, pH, and SS values between input and output of treatment were used to assess IDWW performance. Linear regression was used to determine the connection between the COD and BOD of the wastewater, and the resulting equation (BOD=0.6COD) indicates that the wastewater has a pretty excellent biological treatability. Realized wastewater treatment parameters should fall within the aforementioned tolerance zones.

Table 1. Characteristics of composite wastewater generated for different parameters

Sr. No.	*Parameters*	*Characteristics of composite wastewater generated (Range)*
1.	pH	7.9 - 8.5
2.	COD	720 - 784 (mg/l)
3.	BOD	298 - 340 (mg/l)
4.	Total solids	786 - 1164 (mg/l)
5.	Total dissolved solids	412 - 846 (mg/l)
6.	Total suspended solids	180 - 530 (mg/l)

Take it for google

The following is a ranked list of the inputs used in the model that predicted BOD, COD, and TSS based on the training, validation, and testing data: pH BOD COD TSS. The derived ANN model may be said to be most affected by the TSS concentration. Seventy percent of the dataset is designated as training data, and the network is told to adapt it based on mistake. In a similar vein, while gauging network generalisation and stopping training when generalisation steps improve, 15% of the database is treated as the validating data and 15% data is identified as the testing data. The results show a high degree of agreement with the goals during training, validation, and testing (R-values of 0.93000, 0.86323, respectively) (R-value - 0.86289). The sum of these numbers may be interpreted as an R-value of 0.90317. Now, the network's reaction is enough, so we may utilise simulation to feed in additional parameters.

CONCLUSION

The ANN models were created to evaluate their ability to forecast the quality of river water and IDWW, and they show promise as a prediction tool. In order to fairly assess the performance of the models in water resources, future research should focus on extending the same methodology to various catchments and taking into account relatively lengthy data series. The ANN model is a valid and reliable tool for optimising observational networks by selecting key monitoring locations and making reliable predictions about the quality of river water variables. This area of study is essential for developing accurate models and predictions of water quality as it pertains to land use, water quality, disposal, pollution loading, and ecosystem consequences. Measured and forecasted output variables showed a strong correlation (R-value) of up to 0.9 in these studies.

FUTURE SCOPE

We recommend doing further ANN studies to get a better knowledge of the technology's efficacy in forecasting other water quality parameters, such as nitrate and heavy metals, and the waste water treatment industry's performance.

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