التنبؤ بالاحتياج الكيميائي للأوكسجين في المياه الخارجة من محطة معالجة مياه مجاري مدينة حمص باستخدام الشبكات العصبونية

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الملخص :

تم في هذه الورقة البحثية استخدام الشبكات العصبونية (ANN) للتنبؤ بقيمة الاحتياج الكيميائي للأوكسجين في المياه الخارجة من محطة معالجة مياه مجاري مدينة حمص، وقد استخدمت في البحث بيانات تم تجميعها على مدى عشرة أعوام

من خلال السجلات اليومية لمحطة معالجة مياه مجاري مدينة حمص، تم بناء النموذج بالاعتماد على كل (Q,BOD,COD,SS,SSeff) كمدخلات للتنبؤ بقيمة الـ COD، كما تم تقييم أداء النموذج من خلال اعتماد مقلوب الخطأ لمجموعة التحقيق (Inverse validation error) ، كمعيار حاسم (Fitness) لانتقاء بنية الشبكة الأفضل بالإضافة إلى معايير المفاضلة الأخرى، تم تحديد البنية الأمثل للشبكة العصبونية بعد عدد من المحاولات والأخطاء، وقد أظهرت النتائج كفاءة جيدة للنموذج المقترح بالتنبؤ بقيمةCOD في المياه الخارجة من محطة المعالجة، حيث تم في نهاية هذا البحث التوصل إلى بنية الشبكة العصبونية للتنبؤ بقيمة مؤشر COD وهي (5-20-1) وذلك باستخدام دالة الظل القطعي في الطبقة الخفية والدالة اللوجستية في طبقة الخرج، كما تم اعتماد خوارزمية Quick propagation للتدريب بلغت قيمة تابع الأداء 0.05 كما بلغ متوسط الخطأ الأعظمي للمجموعات الثلاث 18.5و قيمة معامل الارتباط 0.71.

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الكلمات المفتاحية: الشبكات العصبونية ، الاحتياج الكيميائي للأوكسجين، محطة معالجة مياه المجاري.

Prediction of effluent COD for Homs wastewater treatment plant using neural networks

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ABSTRACT:

In this paper the artificial neural networks (ANN) is used for the prediction of chemical oxygen demand.

The data used in this research was collected over ten years through the daily records of the Homs wastewater treatment plant.

The model was built based on the approval of each of the values of (Q.BOD,COD ,SS ,SS out) as inputs to predict the value of the COD, and the performance of the model was evaluated by adopting an inverse validation error for selecting the best network structure in addition to other differential criteria.

The optimal structure of the neural network was determined after a number of attempts and errors, and the results showed a high efficiency of the proposed model algorithms in predicting the value of effluent COD.

As a result of this research, a neural network structure was selected to predict the value of the COD indicator which is (5-20-1) using the Hyperbolic Tangent function in the hidden layer and the logistic function in the output layer, the Quick propagation was used as a training algorithm for training, The value of the performance function was 0.05, and the average error value of the three groups was 18.5, the value of the correlation coefficient was 0.71.

Key Words: Neuronal Network, Chemical Oxygen Demand, Wastewater Treatment Plant.

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1-Introduction:

Domestic wastewater is one of the most significant sources of environmental pollution due to its richness in various pollutants. Therefore, in order to assess the performance of the treatment plant and the quality of the water produced, it is essential to establish a robust and effective model to manage this complex process. Chemical Oxygen Demand (COD) is one of the most widely used parameters to indicate the organic content of water in both wastewater and surface water. COD is defined as the amount of oxygen chemically consumed to decompose the organic matter present in wastewater at standard temperatures. As COD can be used as an alternative to BOD (Biochemical Oxygen Demand), it can be relied upon for various tasks related to the design or operation of treatment plants, such as determining the size of treatment units and the efficiency of certain treatment processes.

COD is a very important parameter when analysing water quality as it provides an indication of the impact of wastewater discharges on the receiving water body. The higher the COD index in the receiving water, the greater the oxidation of organic matter in the water, which ultimately leads to a reduction in the dissolved oxygen (DO) content of the water source. This reduction in dissolved oxygen can lead to anaerobic conditions in the surrounding aquatic environment, which can be very detrimental to the aquatic medium.

Due to the increasing global concern for the environment and public health, the effluent produced by wastewater treatment plants has gained significant importance due to its significant impact on the receiving environment. WWTPs are characterised by their entirely dynamic nature, involving many complex and non-linear processes that are difficult to predict or interpret using a linear statistical or mathematical model. Nevertheless, appropriate modelling plays a crucial role in describing the interactions that occur within the system as a whole.

Rapid population growth has led to urban, agricultural and industrial development, resulting in increased water pollution. This has made the provision of high quality water a challenging and resource intensive task. All this requires the use of new global technologies to monitor and control the operation of wastewater treatment plants in order to improve the quality of the effluent produced and meet the required specifications, as most known digital models do not provide reliable results due to the complex nature of the system

It is worth noting that the high cost and time involved in modelling water quality parameters using empirical models makes it necessary to look for computational applications to address uncertainties and deficiencies in empirical models. Consequently, neural networks have been used to model hydrological flows and wastewater treatment processes. In recent years, Artificial Neural Networks (ANN) have been adopted as an approach for prediction, control, classification, monitoring and simulation of non-linear interactions. The ability of neural networks to consider multiple inputs and outputs, along with their self-learning and adaptive capabilities, makes their application to modelling any system feasible.

Many researchers have successfully used ANN models to predict or classify water quality indicators (WQI). For example, Dogan et al. (2015) used an artificial neural network (ANN) to estimate BOD at the inlet of a wastewater treatment plant. Areerachakul et al. (2011) and Djeddou and Achour (2015) used ANN to estimate the sludge index in an activated sludge treatment plant.

The aim of this research is to develop an artificial intelligence model for predicting the Chemical Oxygen Demand (COD) index of wastewater from the wastewater treatment plant in the city of Homs

2- :material and methods:

1.2 Artificial Neural Networks (ANN):

Artificial Neural Networks are computational techniques designed to simulate the way the human brain performs specific tasks. They consist of simple processing units known as neurons or nodes, which possess a neural characteristic. These units store scientific knowledge and experimental information to make it available for use by adjusting weights.

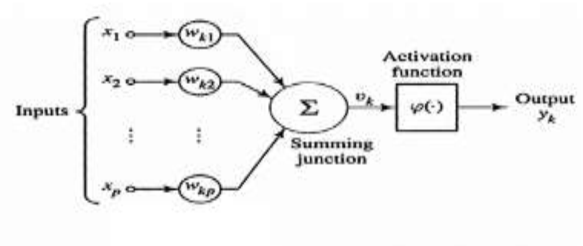

Figure (1) artificial neuron and its basic components

There are many artificial neural networks used in processing patterns of data, and each of these types has a specificity in the architecture and the mechanism of information processing through the number and type of nodes in each layer in addition to the type of activation functions and the mechanism for

2.2 Basic components of an artificial neural network:

Artificial neural networks consist of the following essential components, or at least some of them: [14]

Figure (1) illustrates the mechanism of an artificial neuron and its basic components. ANNs process data in parallel, providing high-speed performance that enables them to solve complex problems involving numerous hypotheses and rapidly changing information effectively.

There are many types of artificial neural networks used in data pattern processing, each with its own unique structure and method for processing information, determined by the number and type of nodes in each layer, as well as the types of activation functions and weight adjustment mechanisms. For this study, a Backpropagation Feedforward neural network was chosen, which has gained significant attention in the field of weather prediction.

These components are: Input Layer, Output Layer, Hidden Layers and Connections (Weights).

1. Input Layer:

The input layer consists of a set of processing units or nodes that distribute the values received from the external environment to the subsequent hidden layer through connections, which will determine the results.

2. Output layer:

This is the final layer, located at the output, where the processing units receive signals from the previous hidden layer to process them computationally in a manner similar to the hidden layers, resulting in final results. This layer, together with the input layer, contributes to the formation of the network's memory.

3. Hidden layers:

These are the intermediate layers between the input and output layers, consisting of one or more layers depending on the size and nature of the problem. They are considered to be the primary element in the storage and retrieval of the network's memory. Research on neural networks shows that there is no standard method for determining the number of hidden layers or the number of neurons in each layer; it is usually done by experimenting until optimal performance is achieved [12].

4. Links (weights):

These are connections between different layers that link the layers together or connect units within each layer to other units by means of weights associated with each connection. The purpose of these links is to transfer weighted data or signals between processing units or layers. Figure (2) illustrates the basic components of an artificial neural network.

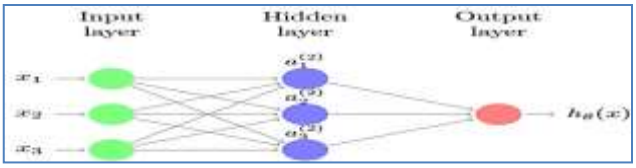

Figure (2): Architectural model of an artificial neural network

The initialization of the weights is a very important process. An initial guess that is closer to the optimal weight values helps the network to generalise faster. However, there is no specific method for making a good initial guess for the weights, so it typically relies on automatically assigning random initial values [5].

5- Transfer Functions:

The transfer function is applied to the output of the neuron and must have the following properties: it should be continuous; it should be differentiable and its derivative should be easy to calculate; and it should be a non-decreasing function [13].

3-2 Study area:

The effluent entering the station undergoes primary filtration to remove heavy suspended solids within the pre-treatment facilities, which also include flow measurement and recording equipment. After pre-treatment, the effluent is settled in radial settling tanks. The effluent from the primary settling tank then passes to surface-aerated biological treatment tanks, followed by the separation of activated sludge in secondary settling tanks.

Part of the activated sludge is returned to the aeration tanks, while the excess sludge is either pumped back to the primary clarifiers for co-sedimentation with the primary sludge, or sent directly to sludge treatment plants.

The effluent from the secondary clarifiers is chlorinated before entering the chlorine contact tank and the chlorinated effluent is discharged directly into the River Orontes for dilution and to initiate its natural advanced treatment. All flows entering the treatment plant are subject to preliminary and preparatory treatment, while the flows directed to secondary treatment are set slightly higher than the daily peak flow during dry weather; the

remainder is discharged directly into the Orontes River. Figure (3) shows an aerial view of the wastewater treatment plant in the city of Homs.
ld be a non-decreasing function [13].

Asi River. Figure (3) shows an aerial view of the sewage treatment plant in Homs city interconnec-tions-weights).(Azzar Tony,2013)

Figure (3) Aerial view of the sewage treatment plant in Homs city

Data source:

Wastewater samples were collected from the wastewater treatment plant in the city of Homs. The study included parameters of the influent water to the plant, which are (BOD, COD, SS, Q, SS_{eff}). In this research, the software program (Alyuda NeuroIntelligence), which is an application for designing neural networks, was used. In addition, the software (SPSS 25) was used for statistical analysis.

The normalization in the model is performed automatically according to equations (1) and (2).

Where:

- x : the true value
- x□$_i$□ : the minimum true value
- x□$_{ax}$: the maximum true value
- min_(scale) : the actual minimum limit of the scaling range
- max_(scale) : the actual maximum limit of the scaling range
- scale_(factor) : the scaling factor
- x_(processed) : the value after processing.

According to most studies and research findings present in the literature, the bipolar range [-1, 1] of the Hyperbolic Tangent function was used for input columns, and the [0..1] range of the Logistic function was used for the output column.

Table (2): Scaling range of activation functions

Output layer activation function	Scaling range
Linear	[-1..1]
Logistic	[0..1]
Hyperbolic Tangent	[-1..1]

According to most studies and research findings present in the literature, the bipolar range [-1, 1] of the Hyperbolic Tangent function was used for input columns, and the [0..1] range of the Logistic function was used for the output column.

Table (3) shows the statistical properties of the variables and the normalization factor for each.

	N	Minimum	Maximum	Mean	Std. Devia-tion	correlation with cod_out
Q(m3/d)	3903	822.00	777178.00	75065.0361	29519.08393	-0.1
BOD(mg/l)	2315	16.00	2696.00	560.6618	335.78836	0.42
COD(mg/l)	3100	41.00	7600.00	939.4932	589.15510	0.93
SS(mg/l)	2926	15.00	4350.00	724.9125	523.95843	0.12
SS_out(mg/l)	2972	3.00	210.00	30.5851	20.66592	0.674
Valid N (listwise)	2012					

4.Results:

The final design of the Artificial Neural Network (ANN) model consists of two parts:

- Network properties: This refers to determining the number of hidden layers and the activation functions used in both the hidden and output layers. In this study, a single layer neural network was used with the hyperbolic tangent function in the hidden layer and the logistic function in the output layer.The Mean Squared Error (MSE) was used as a criterion to evaluate the performance of the model on the three data sets.

- Network architecture: This mainly involves determining the number of neurons in the hidden layer that corresponds to the complexity of the problem under study. There are two search patterns:

- Heuristic search: This starts by filtering a set of designs within a certain range for the number of neurons in the hidden layer, which is suitable for single layer networks.

- Exhaustive search: This tests all possible options within a given range for the number of neurons in the hidden layer and a given step size between them. It is suitable for networks with up to five hidden layers, where guessing and trial-and-error become time-consuming, leading to a quick consideration of the time required for the program to complete the task.

Referentially, a heuristic search can be used due to the lack of information about the complexity of the problem studied and to facilitate the search process by filtering a set of designs within a given range for the number of neurons in the hidden layer between 20 and 100 neurons, using the Inverse Validation Error as a decisive criterion (fitness) for selecting the network architecture, among other comparative criteria. The calculations are repeated (Iteration=300) when running the model (Retrain=1) for one instance. Table (4) shows the results obtained for the best 12 proposed network architectures, indicating that the best structure is

ANN(2-50-1), which means that there are two neurons in the input layer, 50 neurons in the hidden layer and one neuron in the output layer.

Figure (4) shows the absolute error regression of the best proposed artificial neural network model (ANN(5-20-1)) to represent the (COD) values, where the network error values for the training, validation and test sets reached values (18.2, 18.8, 18.18) respectively, with a correlation coefficient of (0.717).

Figure (4): Absolute error regression for the ANN model (5-20-1)

Table (4): Results of the experimental research on the best neural network structure

Architecture Search

ID	Architecture	# of Weights	Fitness	Train Error	Validation Error
	[5-19-1]	134	0.052581	18.31057	19.018337
	[5-12-1]	85	0.052509	18.404882	19.044222
	[5-26-1]	183	0.052048	18.689253	19.213202
	[5-23-1]	162	0.052402	18.314651	19.083292
	[5-16-1]	113	0.052455	17.708342	19.064001
	[5-21-1]	148	0.053016	17.614161	18.86212
0	[5-22-1]	155	0.052421	19.105478	19.076338
1	**[5-20-1]**	**141**	**0.053108**	**18.238043**	**18.829714**

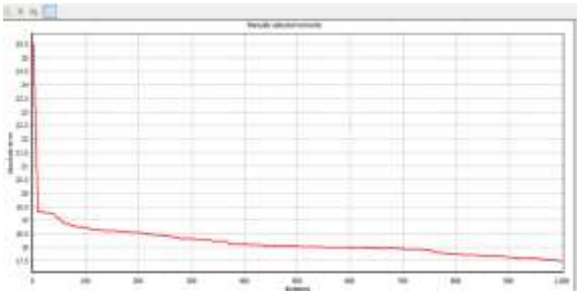

Figure (4): Absolute error regression of ANN model (1-20-5)

4-2- Training the neural network:

The network is trained by providing the training data prepared in the first step and selecting the best ANN architecture (2-54-1) identified in the previous step. The training starts with initial weights (initialising weights), which are modified by repeated calculations to improve the performance of the network and obtain the lowest possible error. With the learning rates and dynamics set, and the stopping criteria chosen to avoid overfitting, training will stop when the Mean Squared Error (MSE) reaches (0.01) or when training is complete after 1000 iterations, whichever comes first. In addition, the Mean Absolute Error and the Sum of Squares Error of the network are calculated according to the chosen training algorithm (fast propagation). Table (5) shows the Mean Squared Errors (MSE) for the selected training algorithm.

Table (5): Mean Squared Errors (MSE) for the selected training algorithm

The Alyuda programme provides the user with a simple query interface through which he can enter the studied inputs and the programme will predict COD_OUT as shown in Figure No. (5).

Table (5): Mean Squared Errors (MSE) for the selected training algorithm

Name	Architecture	Training algorithm	Hidden FX	Output FX	Iterations	Avg training error	Avg test error
Last Trained	[5-20-1]	Quick Propagation	Hyperbolic tangent	Logistic	501	19.18077	18.154783

Figure (5) shows the query interface provid ed by the program

4- CONCLUISON:

- The potential of using artificial neural networks to predict the COD index values in the effluent water from the wastewater treatment plant in the city of Homs.

- A predictive model for COD prediction was developed consisting of five input parameters (Q, BOD, COD, SS, SSeff) and one output parameter (COD) with 20 neurons in the input layer. The Quick Propagation algorithm has been used for training, demonstrating high effectiveness and efficiency compared to other algorithms available in the program.

- It is possible to rely on computational modelling to predict the COD index during the monitoring and control of wastewater treatment plant operations, or when a rapid corrective response is needed in case of unexpected pollution loads.

- The predictive model based on neural networks can give good results under unforeseen operating conditions, such as unexpected organic or hydraulic load shocks.

- Further studies should be carried out on the use of artificial intelligence techniques to predict various treatment indicators related to wastewater treatment plants.

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