Treatability influence of municipal sewage effluent on surface water quality assessment based on Nemerow pollution index using an artificial neural network

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Abstract

Assessing water quality provides a scientific foundation for the development and management of water resources. The objective of the research is to evaluate the impact treated effluent from North Rustumiyia wastewater treatment plant (WWTP) on the quality of Diyala river. The model of the artificial neural network (ANN) and factor analysis (FA) based on Nemerow pollution index (NPI). To define important water quality parameters for North Al-Rustumiyia for the line(F2), the Nemerow Pollution Index was introduced. The most important parameters of assessment of water variation quality of wastewater were the parameter used in the model: biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspension solids (SS), chloride, cl, hydrogen ion concentration, pH, sulfate, SO4-2, nitrate, NO3- and phosphate, PO4-3. Taking these criteria into account, samples of water from the sampling sites were graded as C, indicating the pollutant of the waste treatment. Then the water quality map using neural network model was based on the results of water quality assessment. The results showed that the model North Al-Rustumiyia for line F2 was more efficient and R2 was 0.965 with the impotence parameter was chloride (CL).

1. Introduction

The most valuable freshwater resources have always been rivers and most emerging activities still rely on them[1]. So, one of the main factors and a scientific foundation for enhanced water resources growth and management plans is the river water quality assessment. In order to summarize vast volumes of water quality data into a single number and detect its suitability (for example, great, good, poor, etc.) for various purposes, water quality indices (WQIs, suggested by comparison of real water quality parameters with their corresponding regulatory standards) [2]. This assessment tools are used to evaluate the water quality of the Beiyun River in a systematic manner using 17 parameters of water quality including temperature, pH, conductivity, dissolved oxygen (DO), the chemical oxygen requirement (COD), biochemical demand for oxygen (BOD5), ammonia nitrogen, phosphorus (TP) totals and sulphid. The spatial distribution of WQI values on the Beiyun River was substantially different and the quality of the water upstream and downstream was higher than midstream quality[3]. The principal cause of the degradation of water quality in the Sitnica River is anthropogenic activities, including wastewater discharge, an assessment of the water quality in the Sitnica River by
applying the Canadian Water Quality Index (WQI) and results from the WQI show that it decreases quality as a result of its pollutant impact. This reinforces the urgent need for serious steps to track and control the river properly [4].

US scholarly N. In its 1974 establishment L. Nemerow introduced the Pollution Index (NPI), which has many advantages in the evaluation of water quality: simple mathematical method, easy procedure, integrated effect satisfying, high concentration pollutant effect manifestation and NPI, as an effective approach to assess the water quality of an environment of fresh water. In recent years, many academics and government officials in the field of environment have been very interested in the application of the NPI in water quality assessment[5]. The Zhangze Reservoir water quality was evaluated using the integrated NPI system for the water quality identification. The various assessment methods were analysed and compared and each method’s characteristics determined. Based on these results, we assessed and analyzed the suitability of the water quality evaluation approaches. In every section of water quality monitoring the results produced by the standard Nemerow index method fluctuated considerably [6]. The tool used for the assessment of the Cimanuk water from the years 2013 to 2018 is the Nemerow Pollution Index (NPI). The deterioration of the quality of water in the river Cimanuk showed that the NPI was rising from 1.04 to 7.51. The Cimanuk River has improved from lightly to moderately polluted waters and is not ideal as a potable water source[7]. Moreover, some physicochemical water quality parameters selected were measured and the findings were compared to BIS standards whereby key cations and anionic values were observed below NPI limit according to pollutant status standards. NPI values show that the water of the river is in good condition throughout the year [8]. The assessment of water quality for drinking and irrigation in some marshlands in the Basrah Province to classify major surface water contaminants using NPIs based on the physical and chemical parameters reported in the study region by five monitoring stations during 2014. The findings are compared to Iraqi and WHO requirements and have shown unwanted values for closer purposes [9].

The rising environmental problems have led to an emphasis on the proper operation and regulation of wastewater treatment plants (WWTPs). This could have an effect on the plant at operational risk. The WWTP can result in serious environmental and public health issues because the introduction of polluted effluent to a receiving water bodyshell can result in different pathogens and transfer them to humans and to the marine community if they are introduced into the water before treatment. Environmental laws also set constraints on effluent consistency that any WWTP must follow[10]. From the performance studies Bangalore WWTP revealed that in contrast to removal/reduction in other parameters, the efficiency of both treatment plants was low in the removal of total dissolved solids. The performance studies have shown that the device is optimistic and that aeration tank performance and secondary clarifier in both cases were practically matched. Fresh sludge with higher population of micro-organisms must be recycled and the aerators worked continuously in order to securely discharge the handled effluent into streams, and rivers can even be reutilized to irrigate groundwater [11]. The efficiency of the wastewater treatment facility in Boujaad Area, focused on physical and chemical control, both spatially and temporarily, of raw and refined wastewater in order to diagnose and assess pollution mitigation in this wastewater treatment plant. The study findings show that the efficiency of Boujaad's wastewater treatment plant complies with national and international standards and that its operation was sufficient[12].

The major reasons for lack of state of wastewater treatment facilities in the individual countries are the inadequate coverage of treatment systems in urban and rural areas, poor functionality of wastewater networks, the low architecture, expertise, inability, insufficient support for waste water treatment, the potential for overload of existing facilities and inefficiency[13]. The quality index for wastewater for the calculation of wastewater treatment effluent. Primary consideration of the existence of plant effluents included elevated standards of such requirements limiting the reuse of effluents for human health and the agriculture environment. WWQI is an important method to measure and assess wastewater productivity for decision makers and planners[14].

In order to decide how each of those variables impacts on the BOD regular inlet is used as a basis for the Artificial Neural Network used as a standard prediction model of inputs to waste water biochemical treatment plants with various compositions of daily water quality results[15]. ANNs have
been widely previewed and predicted in many areas, including environmental science and water management, economics, pharmacies, power generation. The findings show that an ANN was an economic model of water quality, and the results show that repetitive neural networks had better results than radial neural networks with multiple components[16]. Due to its accurate, acceptable and promising use of advanced technology, ANN can be used for modeling certain WWTP processes to assist the process efficiency forecasting [17]. ANN's ability to learn basic data generations led to an extensive application of its data in measurement, estimation, practical approximation, classification, and data analysis, given sufficient data samples[18].

The concentration of dissolved oxygen (DO) was estimated based on the relationship between the dissolving oxygen and hydrological parameters using the MLR technique and Back-Propagation Neural Network (BPNN). The findings suggested that the neural network could reliably predict the DO concentration [19]. The ANN can provide a trustworthy forecast model for water quality with land use attributes in accordance with the methods of monitoring water quality, and can find a low-end solution and ensure sustainable development which mainly has an impact on water quality [20]. As water quality deteriorates, serious water quality control activities have been conducted to analyze the ANN methodology that can identify water quality automatically. The findings therefore showed low errors and a high correlation between the parameters measured and predicted and showed a strong ANN ability to forecast water quality parameters [21] Correlation was tested in three separate Korapuzha river stations at Kozhikode in Kerala with Biochemical Oxygen Demand (BOD) and Chemical Oxygen Demand (COD), using Artificial Neural Networks in the research area. The achievement was the high correlation coefficient (R) and low mean square errors of the neural network model provided by BOD and COD. It may also be inferred that ANN is an important modeling method [22]. The ANN-COA hybrid evaluation model developed to forecast a WWTP accurately. This model was developed to optimize model efficiency by using the Artificial Neural Network (ANN). The study showed a greater degree of precision in WWTP prediction and regulation by the hybrid ANN-COA model[23]. Both water amounts and efficiency parameters are agreed by the comparative findings of the optimized urban water model and ANN. The input-output data produced by an integrated urban wastewater model were formed for a feedback-propagation network. CSO dumps and treatment plant effluent are supplied inputs including plumbing and dry-weather and the quantity and consistency are considered. Comparisons between the integrated model and ANN have been shown to be effective with both water quantity and quality parameters [24]. Applications of ANNs are studied in the area of prediction of wastewater treatment, so this study will also discuss a case study documenting detailed simulation work on designing nonlinear neural network prediction models for the Gold Bar WWTP, Edmonton, Alberta [25]. Konya WWTP modeling was explored by using an artificial neural network in Matlab applications with various architectures. Plant efficiency was calculated by using the pH, temperature, COD, TSS and BOD input values with TSS output. The performance and correlation coefficient of the model were compared using Mean Squared Error (MSE) parameters (R). ANN can predict the plant performances of the observed and expected output variable up to 0.96 with correlation coefficient (r)[26]

Furthermore, Fajr Industrial WWTP, located in Mahshahr—Iran has been used to prepare, calibrate, and validate its neural model with qualitative and quantitative characteristics in its units. Primary component analysis (PCA) has also been introduced to enhance the performance of neural network models developed. The unit L-TDS was good model accuracy in estimating the qualitative waste water profile but it did not have enough accuracy to use the biological unit [27] Method has been developed to estimate the odor content with ANN in the WWTP. ANN calculations of the odor concentration of a WWTP based on data of water quality including biological oxygen needs, dissolved oxygen and pH were used. The WWTP water quality and odor data were seasonally calculated in the spring, summer, and autumn as variations on feedback to the ANN model. In comparison with the calculated results was the odor expected by the ANN model and the forecast accuracy was evaluated. Suggestions are provided to improve prediction accuracy [28] Artificial neural network also had to forecast the effluent Chemical Oxygen Demand output of Touggourt WWTP. As an input variable for the neural networks, influential variables like pH, temperature, solid suspended, biochemical oxygen requirements and chemical oxygen requirements
were used. In the phases of learning, evaluation, and checking, the ANN model could predict experimental outcomes at 0.89, 0.96, and 0.87 high correlation coefficient. The overall results showed that the ANN modeling methodology can provide an efficient method to simulate, monitor and forecast WWTP output [29]. Models for artificial neural networks (ANN) to predict the efficiency of the WWTP have been developed based on past data obtained at an average flow rate of 1 million m3/day from an effective traditional treatment plant located in Greater Cairo, Egypt. There are two ANN-based models for plant effluent BOD and SS estimation. The ANN models have been found to be an accurate and stable method to forecast WWTP efficiency [30].

The investigation of the overall performance and evaluation of the effluent quality from Rustamiya sewage treatment plant (STP), Baghdad, Iraq by evaluating the effluent quality index (EQI) on the basis of an artificial neural network (ANN) model which was developed to forecast an effluent quality index based on selected water qualities, it was indicated that the treating sewage effluent quality was within Iraqi quality standards (IQS). The overall performance suggested positive efficiencies and the findings were more successful in the EQI model than relative parameters of 47.3% in the EQI data sets with a high degree of determination coefficient of $R^2 = 99.8\%$ [31]. This paper aims to find the impact of sewage treatment on the quality of surface water based on Nemerow pollution index using Artificial neural network.

2. Case Study Disruption

Al-Rustamiya WWTP is Iraq’s largest treatment plant for wastewater. It is situated on the south side of al-Rusafa in Bagdad, approximately 500 meters from the river Diyala with 400 000 m2 area as shown in Fig. 1 [32]. The inflow line of raw wastewater to plant is Zeplin line. That collect wastewater from Rusafa at design capacity and actual flow 300,000, and 450,000 m3/day respectively. It consists of separate two output lines (F1 and F2). The sewage passes through several stages within the project before being put in the Diyala River. Diyala River is one of the most important rivers in Iraq with a flow rate ranging between 25-650 m3/s [31]. The stage of treatment of this plant are including; screens, grit chambers, aeration tanks, primary sedimentation tanks, secondary sedimentation tanks, chlorination and sludge treatment which treated the raw water physically, chemically and biologically to make it adequate with Iraqi standards for effluent to river [33].

![Figure 1. North Al-Rustumiya plant.](image)

3. Data Collection and Analysis

Data from Al-Rustamiya WWTP is extracted as average monthly reports in five years of laboratory experimentation (2015-2019), biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspension solids (SS), chloride, cl-, hydrogen ion concentration, pH, sulfate, SO4-2, nitrate, NO3- and phosphate, PO4-3. This is data mining to find Nemerow emission index by building models and artificial neural networks with the use of SPSS software Excel-Microsoft Office.
4. Mathematical model and methodology

4.1. Nemerow pollution index (NPI)

After obtaining a water quality index in various surface-water bodies a significant role can be played to minimize pollution problems. In this analysis the use of the Water Quality Index (WQI) was considered useful to determine the total water quality and to exclude the water quality decision. This approach tends to be more standardized and compares water quality assessments of sampling stations [34]. In water quality assessment, although some pollutants’ concentration exceeded standard and induce harm to environment, while the average value of the index is not exceeding the standard. Considering this effect, assessment method of Nemerow pollution index, which combine average value of pollutants with that of maximum value, was used to evaluate the water quality of River [35]. The physical, chemical and biological tests measured by the North Rustumiyia plant for two effluents line (F1, F2) were used. The parameter used in calculation are biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspension solids (SS), chloride (Cl-), ph., SO4-2, NO3- and PO4-3and through these data the monthly Nemerow pollution index rate was calculated for 5 years (2015-2019) depending on Iraqi standard for disposals for rivers. Equation of Nemerow pollution index is specified, each specific use index PIj is represented by a function of the relative values, where [36]:

\[
\text{Relative value} = \frac{C_i(L_{ij})}{(L_{ij \min} + L_{ij \max})^2} (1)
\]

For the cases the contaminant pH:

\[
C_i(L_{ij})^{-1} = \frac{C_i - \left[L_{ij \min} + L_{ij \max}\right]}{L_{ij \max} \left[L_{ij \min} + L_{ij \max}\right]} (2)
\]

And below equation to obtain the value of PI:

\[
\text{PI} = \left[\frac{\text{maximum value}}{\text{mean}} + \frac{\text{maximum value}}{\text{mean}}\right]^{1/2} (3)
\]

The general water-quality index is computed as the weighted sum of the three specific use indices:

\[
\text{PI} = \sum_{j=1}^{3} w_j \text{PI}_j (4)
\]

Where:

\(C_i\) = The parameter level of water quality i
\(L_{ij}\) = The allowable parameter value standard I at a water-use position j.
\(w_j\) = the weight coefficient
\(\text{PI}\) = Nemerow pollution index

Then, results that obtained after complete calculation for Nemerow Pollution Index and classified as shown in Table 2:

| NPI     | Classes             |
|---------|---------------------|
| 0 ≤ NPI ≤ 1 | Standard/Good Quality |
| 1 ≤ NPI ≤ 5 | Lightly Polluted     |
| 5 ≤ NPI ≤ 10 | Moderately Polluted  |
| NPI > 10    | Heavily Polluted     |

4.2. Artificial neural network (ANN)

The aim of a neural network is to measure output values. Neurons (or cells) are processed components conducting basic input value measurements. A neuron transforms the weighted sum of incoming neutron inputs in a nonlinear way to generate the neuron output [38]. ANN consists of layers of artificial neurons or nodes which is in a layer are not linked in the same layer with other nodes. This indicates that only relations between layers and not inside a layer exist. The first layer which receives input information is called the input layer, as shown in figure 2. The last layer that generates information on the output is called an output layer. There are hidden layers between the input and output layers. One or more hidden layers can be found in an ANN. Knowledge is conveyed through...
links between nodes in various layers; hidden layers are used to convert the non-linear input space for computational purposes [17]. Based on the results from Nemerow Pollution Index calculations, a neural network was drawn where the input layers represented the properties of treated sewage and 9 layers of input, while the output was one output layer and represented Nemerow Pollution Index.

![Figure 2. Structure of artificial neural network.](image)

5. Result and discussion

5.1. Assessment of treated wastewater effluent quality

Figure 3 represents the biochemical oxygen demand (BOD) of treated sewage effluent characteristics over twelve months for period five years (2015-2019). The maximum value was 32.52 mg/L in April and minimum value was 22.368 mg/L in December. The values were within the recommended limits of the Iraqi standard (IQS) for disposal into the rivers. April values observed for five years in this month was maximum value that may be back to be that month in spring season that mean warm weather and this is critical condition because the bacterial utilization rate are high and the saturation concentration is low.in addition the lower flows of river [39]. In other hand, comparing with another standard of BOD5 is out of standard is more than 20 mg/L [40], also, the chemical oxygen demand (COD) of treated sewage effluent characteristics over eleven months for period five years (2015-2019) were with in recommended limits of Iraqi standards (IQS) for disposal into the rivers over months of five years, the maximum value was 33.08 mg/L in August and minimum value was 24.412 mg/L in September as showed below in (Figure 4).

![Figure 3. change biochemical oxygen demand (BOD) monthly over five years (2015-2019).](image)

![Figure 4. change chemical oxygen demand (COD) monthly over five years (2015-2019).](image)

The suspension solids of effluent disposal monthly for five years was with standards of Iraqi effluent disposals in rivers. The maximum value observed was 27.89 mg/L in September and minimum value was 21.5 mg/L in June. This variation back to seasonal variation in Iraq; the suspended solids increase in winter season that back to density of rainfall (Figure 5). The quantity of chloride in effluent in
disposals with comparing Iraqi standards was adequate. The maximum value 345.95 mg/L in December and minimum value was 275.04 mg/L in July (Figure 6).

**Figure 5.** change suspension solids (SS) monthly over five years (2015-2019).

Figure 5. change suspension solids (SS) monthly over five years (2015-2019).

The parameter pH referring to acidy or the alkalinity of water. The maximum monthly values for the 5-year evolution of pH were recorded between the period (April and September) that back to activity of factories and industrial processes that associated with activity of people the residual period observed minimum values of pH but surely all records were compatible with Iraqi standards (IQS). in Figure 7 all value that calculate monthly for five years are with the limits of Iraqi standards for disposals in rivers but in other opinion almost all values is more than 7.3 so it doesn’t adequate with the standard and this indicative the raw wastewater influent to plants include industrial wastewater.

Changing Sulfate(SO4) monthly over five years (2015-2019) was out the Iraqi limits these lead to that the raw water have a lot of sulphurous organic matter which passes a lot of processes to produces SO4 which also the quantity of SO4 over 200 mg/L cause sever hindered for sludge digesters (Figure 8).

**Figure 6.** change chloride (Cl-) monthly over five years (2015-2019).

**Figure 7.** change pH monthly over five years (2015-2019).

Figure 7. change pH monthly over five years (2015-2019).

Changing Nitrate (NO3) monthly over five years (2015-2019) was very good comparing with limits of Iraqi standards for effluent disposals in rivers in opposite the value of phosphate were increasing in value in period (October –December) also these value don’t adequate with Iraqi standard (IQS) for effluent disposal in river (figure 9, and figure 10).

**Figure 8.** change Sulphate(SO4\(^{2-}\)) monthly over five years (2015-2019)

**Figure 9.** change Phosphate(P) monthly over five years (2015-2019).
By analyzing data of laboratory tests of treated wastewater that disposal in the Diyala River statistically and over five years from 2015 to the end of 2019 it was found to be the highest level of BOD, CL and SO₄ recorded was in 2017 and were with Iraqi standard (IQS) for BOD, CL and out for SO₄ (figure 11, figure 14 ,and figure 16).in other hand, in 2015 was recorded maximum value in SS, PH. NO₃ and PO₄-3 also were with Iraqi standard (IQS) expect PO₄-3 was out the standard(figure 13, figure 15, figure 17 ,and figure 18) .in addition, in figure 12 appeared the maximum value was in 2016 and was adequate when comparing with (IQS).
Figure 15. change pH yearly over five years (2015-2019)

Figure 16. change Sulphate(SO$_4^{2-}$) yearly over five years (2015-2019)

Figure 17. change (NO$_3^-$) yearly over five years (2015-2019).

Figure 18. change Phosphate (PO$_4^{3-}$) yearly over five years (2015-2019)

5.2. Nemerow pollution index NPI

Figure 19 shows the amount of contamination of treated water monthly and years where the maximum pollution was in December while the highest year was 2019 which gives an indication of pollution of effluent increase with increase temperature of weather and this associated with activity of people also decrease in flow make influent parameters more concentrate. In figure 20 represents Nemerow pollution index changing yearly and as showed above the water quality of effluent be more polluted with progress in years because increasing population in this area serviced that increase the flow that can able to treated it.

Figure 19. change Nemerow Pollution Index (NPI) monthly over five years (2015-2019)

Figure 20. change Nemerow Pollution Index (NPI) yearly over five years (2015-2019)

5.3. Artificial Neural Network ANN
The neural network model was built using a program SPSS where the input layer was eight parameters of treated sewage, the number of hidden layers was two as show in figure 21. The model was successful and the R2 0.965 (figure 22). The most important and influential factor in the model was chloride (CL) and less important parameter that effect in the built model is pH (figure 23).

**Figure 21.** the model of artificial neural network ANN with layers.  
**Figure 22.** predicted value of Nemerow Pollution Index (NPI).  
**Figure 23.** importance of parameters in create the model.
6. Conclusion:
The major results achieve from this research can be explained below:
1- The monthly and yearly changes were within the limits of the Iraqi specification (IQS) except SO4-
2 and PO4-3 which record some values not adequate to the Iraqi specification (IQS).
2- The Nemerow Pollution Index (NPI) showed that the deterioration over the years which need
maintenance and development.
3- A successful ANN model was built based on Nemerow Pollution Index (NPI) where the R2 was
0.965 and the most important influence in the construction of the model was chlorine.

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