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# PREDICTING MUNICIPAL SEWAGE EFFLUENT QUALITY INDEX USING MATHEMATICAL MODELS IN THE AL-RUSTAMIYA SEWAGE TREATMENT PLANT

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## Abstract

Efficient management of treated sewage effluents protects the environment and reuse of municipal, industrial, agricultural and recreational as compensation for water shortages as a second source of water. This study was conducted to investigate the overall performance and evaluate the effluent quality from Al-Rustamiya sewage treatment plant (STP), Baghdad, Iraq by determining the effluent quality index (EQI). This assessment included daily records of major influent and effluent sewage parameters that were obtained from the municipal sewage plant laboratory recorded from January 2011 to December 2018. The result showed that the treated sewage effluent quality from STP was within the Iraqi quality standards (IQS) for disposal and the overall efficiency indicated a positive efficiency of the STP within the order BOD > COD > TSS > chloride. The results revealed that the effluent quality index (EQI) lied under a good water category for both effluent disposal and irrigation use. The multiple linear regression model (MLR) was used for the prediction of EQI and the results provided good estimates for the EQI data sets with a high coefficient of determination ($R^2$=98%). From this analysis, EQI is highly significantly interrelated with TSS, $BOD_5$, and COD within the values 88.9%, 78.6%, and 76.3% respectively. The artificial neural network (ANN) model was developed to predict the effluent quality index based on the selected sewage characteristics. Results provided good estimates for the EQI data sets with a high coefficient of determination ($R^2$=99.8%) and lower relative error and TSS was more effective on the EQI model other than parameters with the relative importance 47.3%. So, the MLR and ANN models were found to provide an effective tool in efficient predicting EQI that can be used effectively to monitor effluent parameters and describe the suitability of treated sewage to quality achieved according to Iraqi quality standards (IQS) for effluent disposal and Food Agriculture Organization (FAO) standards for irrigation purposes.

Keywords: Artificial neural network, Effluent quality index, Multiple linear regression, Sewage treatment plant, Tigris and Diyala River.

## 1. Introduction

Municipal sewage quantities increase due to the population expansion and water supply requirements so, for this reason, there is a need to establish sewage treatment plants (STP) which are designed to remove the suspended and floating substances, biodegradable organic matter and pathogenic organisms to ensure that the effluent pollutants concentrations within the limits established [1, 2]. Effluent discharge from sewage treatment plants should meet the desired guidelines in physical, chemical and microbiological quality to minimize adverse health and environmental impacts with minimum cost in operation and maintenance [3, 4]. The disposal of partially or fully treated effluents into the water sources results in the deterioration of surface water quality in the microbial and chemical properties and the accumulate substances in it, that lead to the depletion of dissolved oxygen [5]. Improving the quality of the treated sewage effluent and reducing the operational costs of municipal sewage treatment plants (STPs) are very complex due to the biological processes influenced by different variables such as raw sewage and flow characteristics that are adopted in the design of these treatment plants [6].

The proper operation and control of STP is receiving increasing attention due to growing concerns about environmental issues, therefore, improper operation of an STP can lead to serious environmental and public health problems that can cause various human diseases [7]. Powerful mathematical tools can be used in STP management to predict plant performance and improve operating control based on previous observations of some key parameters. However, STP modeling is difficult because of the complexity of physical, chemical and biological processes in sewage treatment, where nonlinear behaviours are difficult to be described in linear mathematical models [8]. The objective of developing quality control programs for treated sewage quality is to assist planners and to protect freshwater resources based on treated sewage quality. In general, water quality is assessed by comparing current values with average standards to provide useful information on the quality of spatial and temporal variation [9]. The influent and effluent organic and inorganic parameters are very important in operation and maintenance philosophy, such as biochemical oxygen demand (BOD) which reflects the amount of organic matter that is decomposed by organisms and used to determine and assess the pollution strength of municipal and industrial wastes while chemical oxygen demand (COD) refers to all soluble organic and molecular chemical compounds which are used to measure the content of oxidized organic and inorganic substances in a sewage sample [10, 11]. The total suspended solids (TSS) level in the sewage sample reveals the presence of different types of suspended substances observed in it. Although the BOD, COD and TSS are predominantly removed from the sewage, some organic compounds and TSS still have to be discharged and ultimately will not adequately reflect potential pollution from the wastewater treatment plant and low toxicity weighting factors [12, 13].

The influent sewage strength to the Al-Rustamiya STP varied from medium to high and the average $BOD_5$/COD ratio of the raw sewage was accepted within typical untreated domestic sewage, while the average concentrations of the treated sewage effluent of $BOD_5$, COD, TSS, and chloride were within Iraqi effluent standards and the average $BOD_5$/COD ratios of the treated sewage were high, indicating that sewage needed further treatment [14]. The efficiency evaluation of Al-Rustamiya STP was reflected in the effluent discharged into the Diyala River which indicated that it could not be able to treat the raw sewage and the effluents felt that it exceeded the standard limits which effects of pollution on Diyala aquatic life [15, 16]. The poor efficiency of any sewage treatment plant due to staff skills, operational and maintenance problems needs to improve the performance of STP by training staff and holding them the responsibilities [17]. The suitability assessment of the treated sewage in Al-Rustamiya STP was conducted for irrigation according to its composition and international irrigation water quality standards and the results showed that the treated sewage is suitable for irrigation use [18, 19]. The water quality determination of Diyala River and Al-Rustamiya STP using detection of violation which the results showed that 100% violations and that maximum pollution level of Diyala River based on the parameters (BOD, $SO_4$, $PO_4$, and Cl) and Al-Rustamiya STP had (55-87%) of violation for the years (2005-2007) [20]. In general, sewage treatment plants in Iraq are inefficient due to lack of proper operation and maintenance program and lack of spare parts, as for the STPs in Baghdad city, many researchers observed that these plants discharge the treated effluent and untreated sewage over plant design capacity directly to the Diyala River and Tigris river causing pollution problems [21].

Effluent quality indices (EQI) have been developed to provide useful information on spatial and temporal variability as a rate that reflects the composite influence of different sewage quality parameters on the overall water quality and easy to understand water quality issues by integrating complex data and generated a score that describes water quality status. It may be one of the most effective tools for evaluating and managing water quality that can be helpful for the rapid assessment of any water system [22, 23]. Effluent quality indices incorporate data from different water quality parameters into a mathematical equation that sets a specific level of water quality and gives one value for easy interpretation of control data [24, 25]. Many researchers looked at similar approaches to determine a water quality indicator that can be very useful for managers and decision-makers in planning water resources as well as for comparing the sequence of different sewage treatment [26-28]. The evaluation of the physicochemical and microbial quality of STP effluent for irrigation purposes using the Canadian water quality index showed that the physicochemical quality of STP effluent was good for irrigation in the warm and cold seasons [29]. The effect of the treated and partially treated sewage effluents on river water quality was analysed through the physical, chemical and biological properties of the discharged effluents using the effluent quality index (EQI) [30].

The water quality can be described as somewhat contaminated, which means that the water quality through the sampling points is bad indicating that most of the parameters have deteriorated [12]. The present study aims to investigate the overall performance of Al-Rustamiya STP, Baghdad, Iraq and assess the possibility of using this sewage in irrigation. Also, evaluate the effluent quality of the STP by determining its EQI to find the impacts of the discharged effluents of Al-Rustamiya STP into the Diyala River, and then develop a prediction models for the EQI using the ANN model and multiple linear regression model (MLR).

## 2. Case Study and Data Collection

### 2.1. Study case area description

The case study included the determination of the effluent quality from one of the sewage treatment plants (STPs) in Baghdad city. Baghdad is about 900 km$^2$ with an estimated population of 8 million people in the year 2018. The city is divided into 457 sectors where about 55-75% are served by sewerage systems [18]. There are two working sewage treatment plants (STPs) to treat the collected sewage in the city. The first, Al-Rustamiya STP consists of three plants, South Station (F0) and expansion I (F1), North Station, expansion II (F2) that serve 1.5 million people living in the eastern side of the Tigris river (Rusafa) at design capacity and actual flow as shown in Table 1. The final treated effluent from these plants is discharged into Diyala River and then into the Tigris River. Diyala River is one of the most important rivers in Iraq with a flow rate ranging between 25-650 $m^3/s$ [16]. The second is the Al-Karkh STP that serves the western side of the Tigris river (Karkh) at design capacity and the actual flow as shown in Table 1 and the treated effluent of this plant is discharged directly into the Tigris River as shown in Fig. 1. The effluent from these plants is treated to produce an effluent quality of biological oxygen demand (BOD) and total suspended solids (TSS) as 20 and 30 mg/L, respectively to meet the World Health Organization (WHO) [31]. Nowadays, these plants are operated to reach Iraqi effluent standards for $BOD_5$, COD, TSS and chloride concentrations of 40, 100, 60 and 600 mg/L respectively [32].

**Table 1. Design capacity and the actual flow of STPs in Bagdad [10, 13].**

| STP | Design flow ($m^3$/day) | Actual flow ($m^3$/day) |
|---|---|---|
| **Al-Rustamiya South Station (F0) and expansion I (F1)** | 175,000 | 300,000 |
| **Al-Rustamiya North Station, expansion II (F2)** | 300,000 | 450,000 |
| **Al-Karkh** | 205,000 | 625,000 |


**Fig.1. Al-Rustamiya STP, Tigris and Diyala Rivers within Baghdad City.**

### 2.2. Data collection and analysis

In order to determine the effluent sewage quality from Al-Rustamiya STP, the observation of physicochemical parameters was used to estimate the effluent sewage quality. The data used in this paper was provided by Al-Rustamiya STPs Office-Mayoralty of Baghdad and compared to Iraqi quality standards (IQS) for effluent disposal [32] and Food Agriculture Organization (FAO) standards for irrigation [33]. Five physicochemical parameters were used for raw influents and the treated effluents of STP which were carried out between January 2011 and December 2018 and represented as daily, monthly and annually average values for each parameter. The collected data were biochemical oxygen demand ($BOD_5$), chemical oxygen demand (COD), total suspended solids (TSS), pH, and chloride (Cl).

## 3. Determination of Effluent Quality Index (EQI)

The computation of effluent quality index had been done to judge the remediation extent of sewage and it was calculated by the methods described by Yogendra and Puttaiah [34] in Eqs. (1) to (4) as follows:

A weight (*wi*) was calculated for each parameter assigned according to its relative importance in the overall quality of the influent and treated sewage effluent for disposal and irrigation use.

The relative weight (*Wi*) was computed from the following equation:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

Quality rating scale (*qi*) for each parameter was calculated by dividing its concentration in each sewage sample by its respective standard according to effluent guidelines of the Iraqi quality standards for disposal (IQS) and irrigation use (FAO):

$$q_i = \left(\frac{c_i}{s_i}\right) \times 100 \quad (2)$$

For computing the EQI, the SI is determined for each parameter, then the EQI is indicated by the following equation:

$$SI_i = W_i \times q_i \quad (3)$$

$$EQI = \sum_{i=1}^{n} SI_i \quad (4)$$

Table 2a shows a sample calculation for the determination of EQI according to Iraqi quality standards (IQS) for the disposal of the effluent from Al-Rustamiya STP, while Table 2b is for EQI according to Food Agriculture Organization guidelines (FAO) for irrigation water quality and Table 3 shows the water quality classification based on EQI value.

Monitoring of effluent ammonia ($NH_{4+}$) is as important as other physical and chemical parameters due to all ammonia values after treatment are less than the permissible limits (5 mg/L) according to the Iraqi quality standards [32], and for this reason were not taken by calculating the values of the EQI.

**Table 2(a). Sample calculation of the effluent quality index (IQS) [32].**

| Parameter | Treated sewage effluent | (IQS) standard value ($S_n$) | Weight ($w_i$) | Relative weight ($W_i$) | Quality rate ($q_i$) | $SI_i$ ($W_i$*$q_i$) |
|---|---|---|---|---|---|---|
| **BOD mg/L** | 19.07 | 40 | 3 | 0.23 | 47.68 | 11.00 |
| **COD mg/L** | 40.44 | 100 | 3 | 0.23 | 40.44 | 9.33 |
| **TSS mg/L** | 30.65 | 60 | 2 | 0.15 | 51.08 | 7.86 |
| **pH** | 7.4 | 7.5 | 3 | 0.23 | 98.67 | 22.77 |
| **Chloride mg/L** | 265.52 | 600 | 2 | 0.15 | 44.25 | 6.81 |
| **EQI** | | | 13 | 1.00 | 282.12 | 57.77 |

**Table 2(b). Sample calculation of effluent quality index (FAO) [33].**

| Parameter | Treated sewage effluent | FAO standard value ($S_n$) | Weight ($w_i$) | Relative weight ($W_i$) | Quality rate ($q_i$) | $SI_i$ ($W_i$*$q_i$) |
|---|---|---|---|---|---|---|
| **BOD mg/L** | 19.07 | 30 | 3 | 0.23 | 63.558 | 14.667 |
| **COD mg/L** | 40.44 | 90 | 3 | 0.23 | 44.930 | 10.368 |
| **TSS mg/L** | 30.65 | 45 | 2 | 0.15 | 68.105 | 10.478 |
| **pH** | 7.4 | 7.0 | 3 | 0.23 | 105.748 | 24.403 |
| **Chloride mg/L** | 265.52 | 250 | 2 | 0.15 | 106.207 | 16.340 |
| **EQI** | | | 13 | 1.00 | | 76.256 |

**Table 3. Water quality classification based on EQI value [35].**

| Water quality index level | Water quality status |
|---|---|
| **<50** | Excellent |
| **50-100** | Good water |
| **100-200** | Poor water |
| **200-300** | Very poor water |
| **>300** | Water unsuitable for drinking |

## 4. Concept of Mathematical Models Prediction

### 4.1. Multiple linear regression model (MLR)

Multiple regression explains the relationship between multiple independent variables (predictive) and the dependent variables [11]. The dependent variable is modelled as a function of several independent variables with corresponding coefficients, along the constant term. The multiple linear regression (MLR) aims to model the linear relationship between the explanatory (independent) variables and response (dependent) variable. The degree of linear correlation between any variables in this analysis is measured by the coefficient of determination ($R^2$) which is used to measure the amount of variance in the result and can be explained by the variance in independent variables where it always increases when more predictors are added to the MLR model even though the predictors may not correlate with the result variable [36].

### 4.2. Artificial neural network (ANN)

It is a nonlinear modeling method capable of handling many independent variables (inputs) to determine one or more dependent variables (outputs). It can find and identify complex patterns in data sets that may operate by simulating at a simplified level, human brain activities and it could be useful in predicting complex environments [36, 37]. The ANN training process is designed to develop an internal set of features to classify data, provide incomplete data, sacrificial results, and less susceptible to abnormal values. A measurable function between the input and output vectors can be approximated with a multi-layered neural network by selecting an appropriate set of connected weights and transfer functions. The ANN has achieved this through a large number of highly correlated processing elements (neurons) to solve many specific problems, such as forecasting, predicting and pattern recognition [38].

The ANN structure used in this study is the feed-forward pattern, where the information is transmitted in a forward direction only and it is composed of a number of artificial neurons that are ordinarily arranged in layers. A layer of input units is connected to an output layer through one or more intermediate layers called hidden layers. The core element of the neural network is the artificial neuron, which consists of three main components: weights, bias, and activation function [36]. The ANN connections between neurons are directional and the information is transmitted only in one direction with varying coefficients or weights representing the relative influence of the different neuron inputs to other neurons shown in Fig. 2. The weighted sum of the inputs is transferred to the hidden neurons, where it is transformed using an activation function and the outputs of the hidden neurons act as inputs to the output neuron where it undergoes another transformation [38, 39].

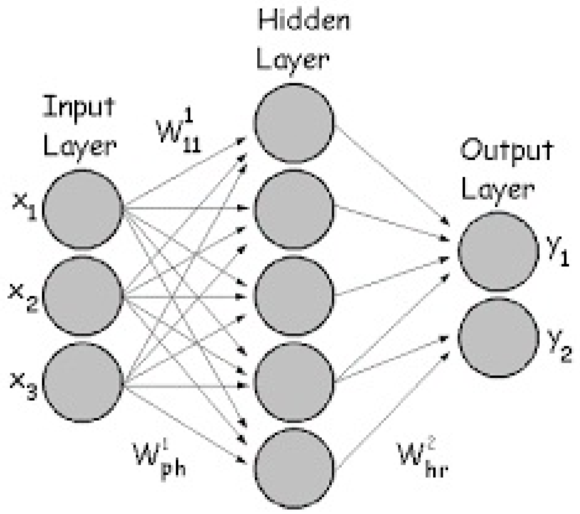


**Fig. 2. Structure of the artificial neural network layer.**

## 5. Results and Discussion

### 5.1. Performance assessment of STP

Table 4 shows the influent sewage concentration values entering Al-Rustamiya STP and the treated effluent during the study period according to the physicochemical tests made by Al-Rustamiya laboratory STP for $BOD_5$, COD, TSS, pH, and chloride using statistical package for social sciences (SPSS version

24). The strength of the raw sewage entering the STP varied from medium to high and the influent sewage $BOD_5$/COD ratios showed a ratio within permissible limits that can be effectively treated biologically [40, 41] as shown in Table 5. The treated sewage effluent characteristics were within the recommended limits of the Iraqi standard (IQS) for disposal into the Diyala River. The observations carried out on this river refer to the deterioration of its water quality caused by the disposal of untreated sewage due to the overflow capacities which are in excess of the STP design capacity. The average $BOD_5$/COD ratio for the treated effluents was relatively high indicating proportions of non-biodegradable content in the treated effluent as shown in Table 6 [12]. The overall efficiency was calculated by considering the parameters $BOD_5$, COD, and TSS of the influent to STP and effluent from the secondary clarifier. Results showed that the $BOD_5$, COD, and TSS reduction were high, and therefore, the efficient removal of $BOD_5$ > COD > TSS [42-44]. Actually, a significant variation was noted in the overall removal efficiency of treatment plants for the study period due to the deterioration of effluent treated sewage into the Diyala River which indicating poor efficiency in terms of parameter removal [13, 16, 45].

**Table 4. Sewage characteristics at Al-Rustamiya STP during (2011-2018).**

| Parameter | Influent raw sewage | | | Effluent treated sewage | | | Efficiency % |
|---|---|---|---|---|---|---|---|
| | min. | max. | avg. | min. | max. | avg. | |
| **BOD mg/L** | 188.88 | 260.9 | 232.31 | 15.8 | 22.13 | 19.07 | 91.79 |
| **COD mg/L** | 361.73 | 475.3 | 400.33 | 33.12 | 48.69 | 40.44 | 89.89 |
| **TSS mg/L** | 190.33 | 278.6 | 231.23 | 19.45 | 41.68 | 30.65 | 86.74 |
| **pH** | 7.08 | 7.35 | 7.22 | 7.23 | 7.54 | 7.4 | |
| **Chloride mg/L** | 298.15 | 342.85 | 328.81 | 222 | 297.06 | 265.52 | 19.25 |
| **BOD/COD** | 0.49 | 0.72 | 0.59 | 0.35 | 0.55 | 0.49 | |

**Table 5. Classification of untreated sewage strength.**

| Parameter | Strength [40] | | | Strength [41] | | |
|---|---|---|---|---|---|---|
| | Low | Medium | High | Low | Medium | High |
| **$BOD_5$ mg/L** | 110 | 190 | 350 | 100 | 200 | 400 |
| **COD mg/L** | 250 | 430 | 800 | 175 | 300 | 600 |
| **TOC mg/L** | 80 | 140 | 260 | 100 | 200 | 400 |

**Table 6. Sewage characteristics vs various parameters ratios [40].**

| Type of sewage | $BOD_5$/COD | $BOD_5$/TOC |
|---|---|---|
| **Untreated** | 0.3 – 0.8 | 1.2 – 2.0 |
| **After Primary Settling** | 0.4 – 0.6 | 0.8 – 1.2 |
| **Final Effluent** | 0.1 – 0.3 | 0.2 – 0.5 |

## 5.2. Assessment of effluent quality index (EQI)

The effluent quality index (EQI) was proposed to quickly compare of the effluent quality of the treatment process at different times, to represent the final effluent quality and to assess whether it would be suitable for the final destination [25, 26]. In this study, EQI was calculated to describe the suitability of treated wastewater for surface water disposal and irrigation use that help facilitate decision-making to avoid any adverse effects on the surrounding environment and user health [46]. By using IQS for effluent disposal, the results showed that the average monthly EQI values during study period ranged from minimum value 53.06 in May to maximum value 67.16 in November with an average value of 57.4 while annual EQI values ranged from minimum value 53.83 in 2017 to maximum value 63.43 in 2014 with an average value of 57.83 which indicating that the monthly and annual EQI values fall within a good water range as shown in the Table 2(a), Figs. 3 and 4. While, for irrigation purpose using FAO, the results showed that the average monthly EQI values during study period ranged from minimum value 69.54 in September to maximum value 88.42 in November with an average value of 76.05 while annual EQI values ranged from minimum value 71.34 in 2015 to maximum value 83.38 in 2012 with an average value of 76.33 indicating that the monthly and annual EQI values fall within a good water range as shown in the Table 2(b), Figs. 3 and 4. As for using the effluent from Al-Rustamiya STP for irrigation because the treated water specifications meet with the specifications of irrigation water [2, 4].

From the monthly and annually results mentioned above, and according to the Iraqi standard standards for disposal of treated wastewater to river sources and the FAO standard for agricultural purpose, the main reason for the results fluctuation is due to increase the amount of influent flow to the STP especially during the runoff period, which directly effects on changing the design criteria in the primary and secondary treatment and thus effluent disposal specifications that do not meet the standard specifications [30]. Also, the EQI values calculated by FAO are considering more reliable and accurate than IQS because the permissible limits are less than the limits permitted by the Iraqi specifications. But the reality of the state of the treated effluent disposal to the Diyala River does not agree with these EQI results and the reasons are due to these data were taken before and after the sewage treatment plant which do not represent actual wastewater that exceeds the STP design capacity and disposal to the Diyala River, in addition to the inaccuracy of laboratory equipment and the lack of personnel experience working in the wastewater treatment plant laboratory [47, 48].

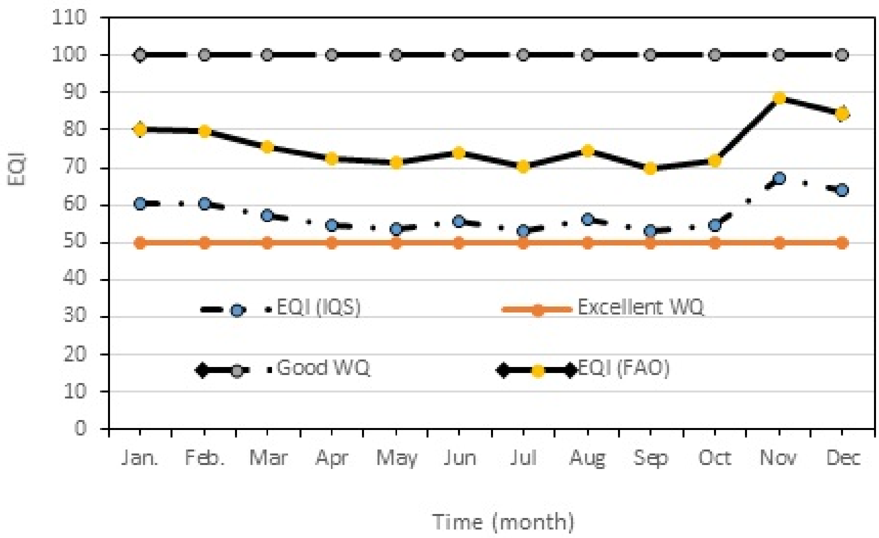


**Fig. 3. Monthly variation of the effluent quality index during (2011-2018).**

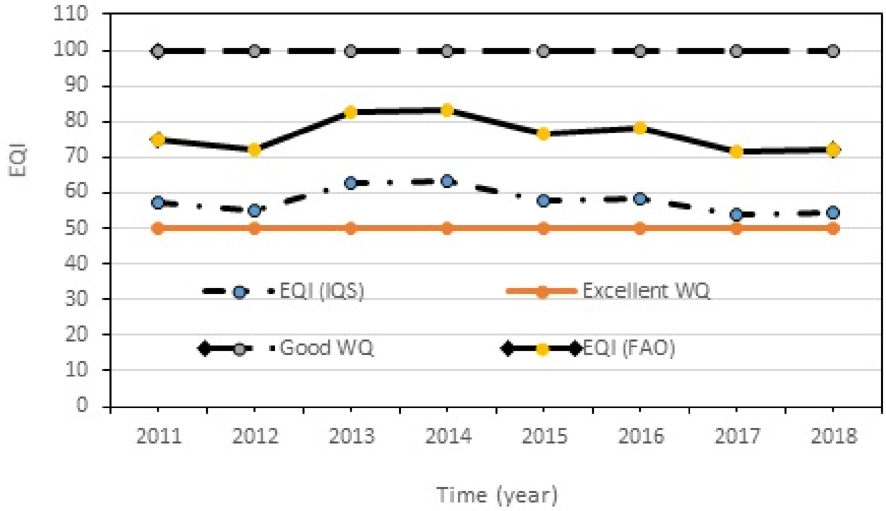


**Fig. 4. Annually variation of the effluent quality index during (2011-2018).**

## 5.3. Multiple linear regression model (MLR)

The correlation analysis measures the convergence of the relationship between the selected variables especially if the correlation coefficient is closer to +1 or -1, it means that the ideal linear relationship between the two variables, therefore, this way analysis attempts to establish the nature of the relationship between the water quality parameter and EQI [36]. The physicochemical parameters of the treated wastewater effluent after secondary treatment for eight years (2011-2018) were used as independent variables to construct the multiple linear regression model for predicting the EQI value if concentrations of treated effluent were available. The results showed that the linear correlation degree between any two of the sewage quality parameters and EQI measured by correlation coefficient ($r$) is presented in Table 7. EQI is observed that the highly significant interrelated with TSS, $BOD_5$, COD with the values 88.4%, 78.6%, and 76.3% respectively and low significant interrelated with pH and chloride.

**Table 7. Correlation coefficient matrix of sewage treated effluent.**

| Parameter | EQI | BOD | COD | SS | pH | Chloride |
|---|---|---|---|---|---|---|
| **EQI** | 1.000 | | | | | |
| **BOD** | .786 | 1.000 | | | | |
| **COD** | .763 | .453 | 1.000 | | | |
| **TSS** | .884 | .537 | .524 | 1.000 | | |
| **pH** | .264 | .173 | .324 | .069 | 1.000 | |
| **Chloride** | .258 | .113 | .342 | .049 | .457 | 1.000 |

The prediction equation for EQI can be written using the multiple linear regression model (MLR) by adopting the dependent variable (EQI), and independent variables of the treated effluent ($BOD_5$, COD, TSS, pH, and chloride) as shown in Eq. (5) with a coefficient of determination ($R^2$ = 98%).

$$EQI = -0.001 + 0.578BOD_{mg/L} + 0.231COD_{mg/L} + 0.257TSS_{mg/L} + 3.08pH + 0.026Chloride_{mg/L} \quad (5)$$

## 5.4. Artificial neural network

Artificial neural networks (ANN) were used to predict the performance of Al-Rustamiya STP and the future treated effluent values based on the past information of the influent raw sewage in order to control the plant process with less operating problems [3, 37]. The SPSS software was used to develop a model for predicting EQI and through trial and error, the optimal network has been reached. The input layer data contained the total number of sample 69 which were divided into three parts such as training, testing, and holdout and after several attempts to run the ANN program to obtain higher coefficient of determination with lower relative error at (66.7% for training, 21.7% for testing, 11.6% for holdout). The activation function used in this model was standardized for the input layer, Hyperbolic tangent for the hidden layer, and identity for the output layer. The developed model contained one hidden layer with three nodes. Figure 5 shows the ANN model architecture that represents the prediction of EQI in the Al-Rustamiya STP.

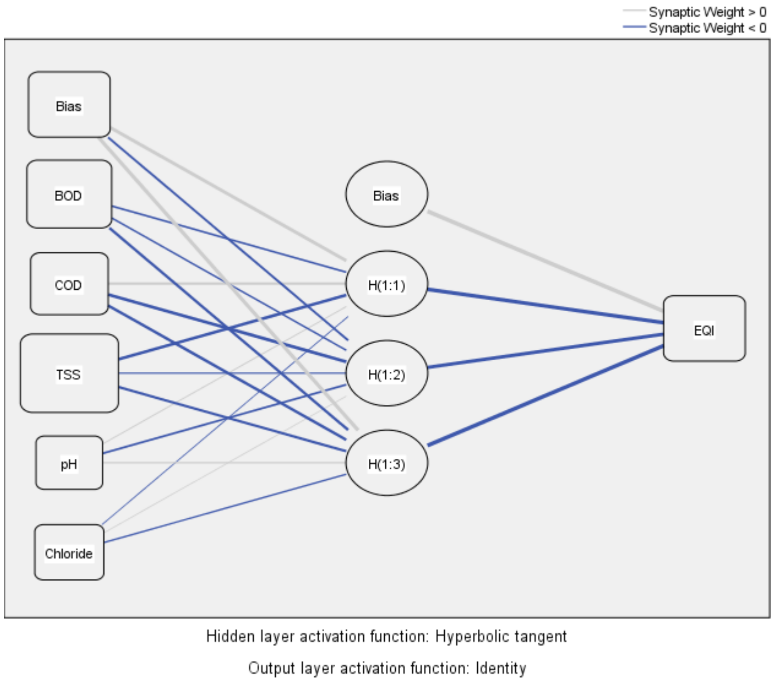


**Fig. 5. ANN model architecture.**

Figure 6 shows the observed and predicated EQI values for Al-Rustamiya STP from the ANN model and which can be written as in Eq. (6) with a coefficient of determination ($R^2$=99.8%).

$$\mathrm{EQI}_{Predicated} = 0.48 + 0.99 * EQI_{Observed} \quad (6)$$

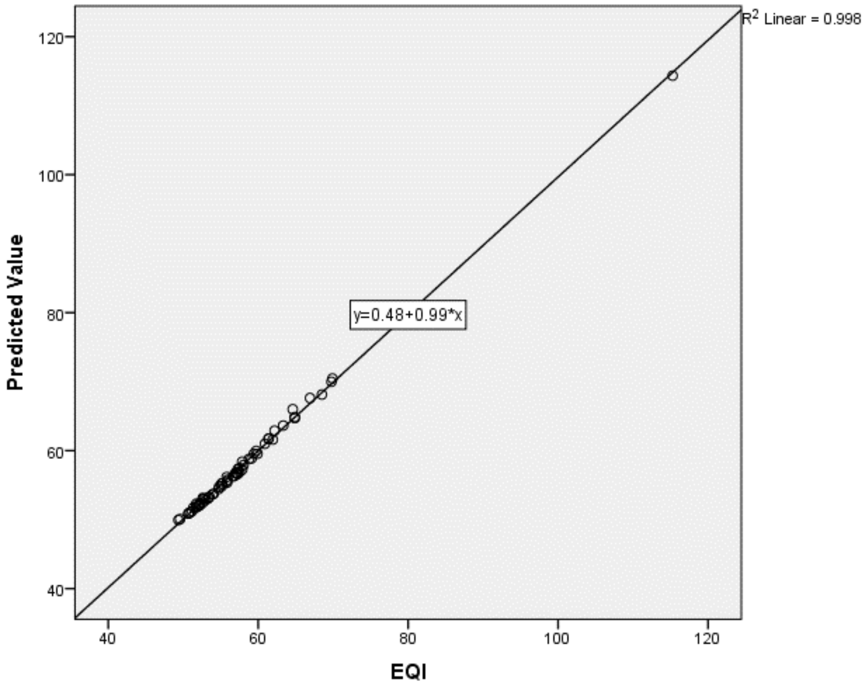


**Fig. 6. EQI observed vs predicated value.**

With this equation, the future EQI for Al-Rustamiya STP can be predicted if some actual EQI values are available at a high coefficient of determination ($R^2$=99.8%) with lower relative error and the results showed a very good accuracy and predictive capacity for this model. The significance of the predictor variable (independent) on the neural network output and their sensitivity can be measured by translation of the neural network connection weights [37].

The importance of independent variables and the degree of their effect on building the EQI equation, Eq. (6), with the dependent variable, where all the variables available by the laboratory of Al-Rustamiya STP were used in the SPSS program for the purpose of building the equation. So, Fig. 7 represents the relative importance of the independent variables by ANN program in building an EQI model as TSS, $BOD_5$, COD, chloride, and pH with 47.3%, 28.1%, 17.6%, 5.3%, and 1.8% respectively, indicating that TSS is more effective and influential on the EQI model than the other parameters. These results also agree with the correlation analysis as EQI was highly significant interrelated with TSS, $BOD_5$, and COD. But it is clear that the plant is not operating as efficiently as required below the required level and needs to be improved due to lack of technical staff, operational problems, and maintenance program that have resulted in poor performance of treatment units [49].

The higher coefficient of determination with lower relative error for the ANN model indicates that more effective and most significant influential prediction of the EQI equation from the multiple linear regression model [39].

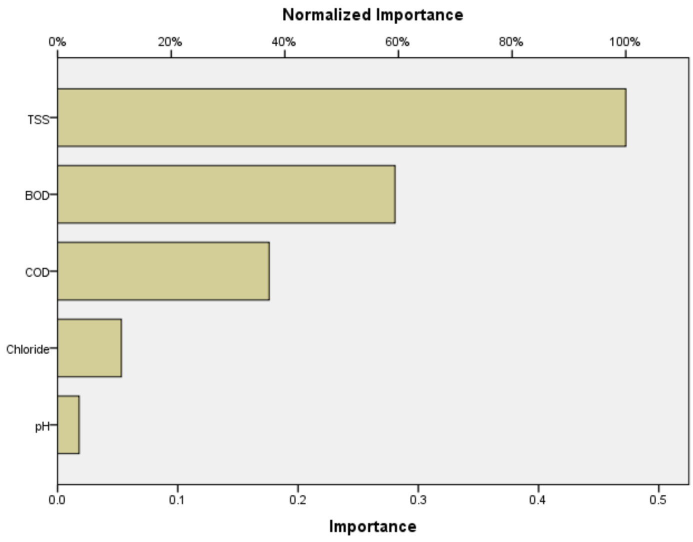


**Fig. 7. Independent variable importance of the ANN model.**

## 6. Conclusions

The most important conclusions reached in this study are as follows:

- The performance assessment of municipal sewage treated effluent quality from Al-Rustamiya STP in relation to the organic and inorganic matter treatment indicated a positive efficiency of the system with the overall efficiency is in the order BOD > COD > TSS > chloride and, also, the effluent quality suitable for surface disposal and irrigation purposes.
- The results revealed that the effluent quality index (EQI) lied under good water category for both disposal requirements in agreement with IQS and FAO.
- EQI was found that the correlation for the interrelation between different parameters with highly significantly correlated with $BOD_5$, COD, TSS, pH, at 0.05 Level and results indicated that using such indices can help in decision making for reuse purposes and assessing the improvement in the treatment procedure.
- The multiple linear regression model (MLR) found a high significantly correlated between EQI and different parameters at 0.05 level with coefficient of determination ($R^2$=98%) and EQI is highly significant interrelated with TSS than the other parameters.
- The artificial neural network model (ANN) provided good estimates and efficient to predict EQI values with a high coefficient of determination ($R^2$=99.8%). TSS was more effective on the EQI value than the other parameters as the relative importance was 47.3%.

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Engineering Department/Engineering College-University of Baghdad for their valuable support to complete this work.

## Nomenclatures

| | |
|---|---|
| *Ci* | The concentration of each parameter in each sewage sample |
| *n* | Number of parameters |
| *qi* | Rating based on the concentration of the ith parameter |
| *Si* | Iraqi standard for effluent disposal |
| $SI_i$ | Sub-index of ith parameter |
| *wi* | weight of each parameter |
| *Wi* | Relative weight |

### Abbreviations

| | |
|---|---|
| ANN | Artificial neural network |
| EQI | Effluent Quality Index |
| FAO | Food Agriculture Organization |
| IQS | Iraq quality standard |
| MLR | Multiple linear regression |
| STP | Sewage treatment plant |
| WHO | World Health Organization |

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