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# Modeling of Electrical Energy in Industrial Wastewater Treatment Plant with Traditional and Artificial Neural Network Approaches

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**Abstract**

The rapid development of industries and the establishment of numerous industrial parks have initiated several environmental issues in recent decades. The environmental standards and rules issued by the environmental organization for increasing the quality of treated wastewater on the one hand and increasing the energy price on the other hand have caused the energy management debate to be of particular importance. The main aim of energy management is to minimize the high energy consumption in industrial wastewater treatment plants (IWWTP). In this paper, the electric power consumption of the IWWTP in Amol's industrial park (AIP) was measured by implementing both traditional and advanced methods (using artificial neural networks). In the first step, total energy consumption, involving energy used by flow or aeration pumps and mixers, was calculated through an energy activity diagram, mathematical equations, and mass balances. In addition, linear regression equations for electrical energy consumption were estimated based on the amount of oxygen needed with an appropriate correlation coefficient. In the next step, a three-layer artificial neural network (ANN) with the Leonberg-Marquard training algorithm was employed. Various parameters, including chemical oxygen demand (COD), biological oxygen demand (BOD), total phosphorus, total nitrogen, mixed liquor suspended solids (MLSS), and the flow rate (Q) were employed in four models to predict the electrical energy consumption of the IWWTP. Results showed that COD, MLSS, and Q can be considered as the most important selective indices for the determination of energy consumption by which the highest correlation coefficient and the lowest error rate of 0.928 and 0.0098 were obtained, respectively.

## 1. Introduction

With the advancement of industries in recent decades, industrial parks either have been constructed or are under construction around cities. According to the law, commercial units that produce pollution should be separated from the urban areas and be established in industrial parks around cities (Chae KyuJung and Kang JiHoon, 2013). To protect the environment, all industrial parks are required to treat their wastewater, and after reducing the physical, chemical, and biological pollution to environmentally acceptable levels, they would be allowed to

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enter their wastewater into the environment (Saghafi et al., 2016). Industrial wastewater contains organic matter and toxic pollutants (Munter, 2003a, 2003b), Therefore, the wastewater treatment systems of industrial parks should have required efficiency so that their effluent does not damage the environment (Halkos and Tzeremes, 2012). In the wastewater industry, the public attention is more focused on the standard quality of effluent and there is little management of energy consumption (Metcalf et al., 1991). At first glance, it does not seem necessary to reduce energy consumption in the water and wastewater system, but when the annual energy cost and significant placement of energy equipment in the water and wastewater system are taken into account, it can be concluded that saving energy in the water and wastewater treatment systems is an absolute necessity (Campello et al., 2021). The reduction of energy sources and the rise of energy prices in the world, especially in under-developing countries, as well as environmental problems, such as global warming and rising temperatures, air changes and drought intensification, etc (Gikas, 2017), caused by the high consumption of fossil fuels, have made energy management in the sewage industry to become severely important (Nabavi-Pelesaraei et al., 2017). Considering the economic developments and the increase in the price of energy, there have been many changes in water consumption, quantity, and the quality of sewage produced by factories (Omer, 2008). Most wastewater treatment systems use electrical energy, therefore, 25 to 40 percent of the total cost of the wastewater treatment process in a wastewater treatment plant is spent on the energy sector (Saghafi et al., 2020). This has led designers of the new wastewater treatment methods to focus on reducing energy consumption (Zhang et al., 2012).

The first step in energy consumption management is to determine the amount of energy used and the factors and parameters affecting it (Sonesson et al., 2000). Traditional or intelligent software can be used to determine energy consumption in a treatment plant (Saghafi et al., 2015). In traditional methods, the total energy consumption of a treatment plant, including the energy used by pumps, mixers, and aeration, is calculated by mathematical equations and mass balance (Saghafi et al., 2016). Determination of the total electrical energy consumed by the wastewater treatment plant in a traditional way is very complex and time-consuming. Linear equations cannot efficiently estimate electrical energy due to the dynamic behavior of the treatment plant and the interaction of factors affecting electrical energy consumption (Saghafi et al., 2018). Therefore, implementing a quick and practical approach like an ANN can be very useful in modeling the electrical energy consumed by plants since, in addition to needing less time, it is more accurate (Saghafi et al., 2019). ANNs are non-linear computing systems that mimic the natural neural processes (Sarkar et al., 2009). Like the human brain, the ANNs consist of nodes and communications, which makes ANNs a creative and promising solution to the problem of the relevance of output variables to their input into complex systems (Dawson and Wilby, 2001). Neural network technology is mostly employed for prediction (Dawson and Wilby, 2001). Multilayer perceptron (MLP) neural networks are one the most practical methods in ANN (Fischer, 2006).

Various algorithms can be used in ANN to achieve the best result from the given input. The network will be trained by these algorithms to generate the desired output. In each algorithm, different correlations and hidden patterns will be applied to the given data to classify and cluster the raw data. The standard backpropagation algorithm (BPNN), conjugate gradient (CG), and Levenberg–Marquardt algorithm are some examples of the most well-known algorithms for training procedures (Falah Nezhad et al., 2016; Fischer, 2006). The standard backpropagation algorithm works by adjusting the weights in the steepest descent direction in which the performance function is decreasing most rapidly. In the CG algorithms, a search is performed along conjugate directions to achieve a faster convergence than the steepest descent directions. The Levenberg–Marquardt algorithm is also a training algorithm that is designed to approach second-order training speed without having to compute the Hessian matrix. Among these algorithms, BPNN is the most popular network, especially in the case of non-linear approximation (Kashaninejad et al., 2009). Each BPNN consists of an input layer, an output layer, and one or more hidden layers. It works backward from the output layer to adjust the weights accordingly and reduce the average error across all layers. This process is repeated until the weights reach their optimal values and the error between the output of the network and the desired output is minimized (Aydiner et al., 2005). The main task in designing a BPNN network is to find the appropriate number of layers and also the number of neurons in each layer in a way that the overall network error minimizes.

ANN is commonly used as a very useful tool in a wide range of topics and areas of great complexity (Boger, 1992; Falah Nezhad et al., 2016; Maier and Dandy, 2000). It has also been widely used in environmental issues such as predicting the river flow model (Teschl and Randeu, 2006), prediction of wastewater effluent quality in treatment plants (Khalil et al., 2011), assessing the performance of IWWTP, and predicting and locating appropriate landfill sites (Ali Abdoli et al., 2012). However, according to our knowledge, no study has been carried out on the prediction of energy consumption in wastewater treatment plants using ANN so far. Considering the importance and the necessity of energy management, the amount of electrical energy consumption in IWWTPs was modeled in this study. Since the first step in energy consumption management.

is prediction, energy consumption was investigated by employing a traditional method using an activity diagram as well as a neural network. To determine the energy consumption traditionally, the electric power consumption in pumps, mixers, and electric motors was determined separately. Also, the electrical energy consumed in the aeration section was calculated by implementing mass equations. After that, various models of a three-layer neural network were developed to predict the electrical energy consumption of the wastewater treatment plant of Amol’s industrial park. First, 6 input variables were selected, including COD removal, BOD removal, nitrogen removal rate, phosphorus removal rate, inlet flow, and MLSS, and then further models were also considered to assess the sensitivity of the models and the impact of input parameters.

## 2. Materials and Methods

### 2.1. Data Collection

The wastewater treatment plant of AIP works using a hybrid filtration method, which includes an upflow anaerobic packed bioreactor (UAPB) as an anaerobic treatment and the integrated fixed-bed activated sludge (IFAS) as an aerobic treatment process. The main components of this treatment plant include a screening unit, grit removal unit, scum removal, equalization tank, UAFB tank, aeration tank, sedimentation tank, disinfection tank, and sludge digestion. The seven active industrial groups involved in the AIP included metal industries, chemical and rubber industries, non-metallic mineral industries, electrical and electronic industries, wood and paper industries, food and beverage industries, and textile and clothing industries (Campello et al., 2021). In total, there were 194 utilized units on the site. Table 1 illustrates the electrical equipment employed in the wastewater treatment plant at AIP.

**Table 1**. The existing electrical equipment used in the IWWTP of Amol

| Unit | Description | Number of units | Equipment | Number of equipment | Power (kW) | Working Time ($h.day^{-1}$) |
|---|---|---|---|---|---|---|
| 1 | Bar screen | 1 | Pump | 1 | 0.55 | 24 |
| 2 | Equalization tank | 1 | Pump | 3 | 3.6 | 12 |
| | | | Mixer | 1 | 0.8 | 14 |
| 3 | Aeration tank | 4 | Blower | 4 | 22 | 12 |
| 4 | Disinfectant system | 1 | Dosing pump | 1 | 0.031 | 12 |
| | | | Mixer | 3 | 0.18 | 8 |
| 5 | Sludge thickening | 1 | Pump | 2 | 2.2 | 16 |
| 6 | Sludge digestion | 1 | Pump | 1 | 2.2 | 16 |
| 7 | Sludge Storage | 1 | Mixer | 1 | 0.4 | 12 |
| 8 | Filter Press | 1 | Compressor | 2 | 8 | 12 |

## 2.2. Determination of electrical energy in IWWTP

### 2.2.1. Traditional method

Determination of the consumed electrical energy in the traditional manner was carried out via the energy efficiency diagram in the wastewater treatment plant. The dynamic behavior diagram (shown in Fig. 1) illustrates the consumption of electrical energy in the wastewater treatment plant of AIP. The major consumers of electrical energy in the wastewater treatment plant are pumps and mixers, especially in the aeration process. The electricity consumption of treatment plant equipment, such as pumps and mixers, was calculated through mathematical equations. For example, in order to obtain the amount of energy consumed in the aeration process, first, the kinetic coefficients of biological growth in the aeration tank were found, and then by establishing the relationship between biological activity, nutrient intakes, and the amount of oxygen demand, electrical energy consumption was determined as the linear regression.

In the given flowchart, $E_m$ is the electrical energy consumed in mixers calculated by Equations 1.

$$E_m = \frac{P \times T}{Q} \quad (1)$$

where $E_m$ is the electrical energy in $kWh.m^{-3}$, P is the electrical power of the pump or motors in kW, T is the duration of using the pump or motor in $h.day^{-1}$, and Q is the total amount of influent wastewater ($m^3.day^{-1}$)(Singh et al., 2009) (Singh et al., 2012).

$E_p$ also represents the electrical energy consumed in pumps, calculated by Equations 2.

$$E_p = \acute{E}_p = \sum_{i=1}^{n} E_i \quad (2)$$

Where $E_i$ is the energy of each pump calculated using Equations 3 and 4.

$$E_i = \frac{100}{\eta} \mathrm{Q}\, \Delta \mathrm{p} \quad (3)$$

$$\Delta \mathrm{p} = \rho \mathrm{g}\left( 0.001 * \dot{\mathrm{m}}^{1.89} \mathrm{d}_{\mathrm{pipe}}^{5.01} \mathrm{L}_{\mathrm{pipe}} + \Delta \mathrm{Z}\right) \quad (4)$$

Where n is the number of pumps, η is the pump efficiency, Q is the sewage flow ($m^3.day^{-1}$), and Δp is the pressure drop in meters (calculated by Equation 4). In equation 4, ΔZ is the difference between the inlet and outlet head (m), $L_{pipe}$ is the length of the pipe (m), $d_{pipe}$ is the pipe diameter (m), and $\dot{m}$ is the mass flow.

$O_2$ is the amount of oxygen needed for food intake corresponding to the carbon source (kg/day) can be calculated through equations 5 and 6.

Where $S_\circ$ is the inlet COD (mg/L), S is the COD of outlet flow from the aeration tank (mg/L), and Y is the efficiency coefficient.

$$O_2 = \mathrm{Q}(\mathrm{S}_\circ - \mathrm{S}) - 1.42\dot{\mathrm{m}} \quad (5)$$

$$\dot{\mathrm{m}} = \mathrm{YQ}(\mathrm{S}_\circ - \mathrm{S}) \quad (6)$$

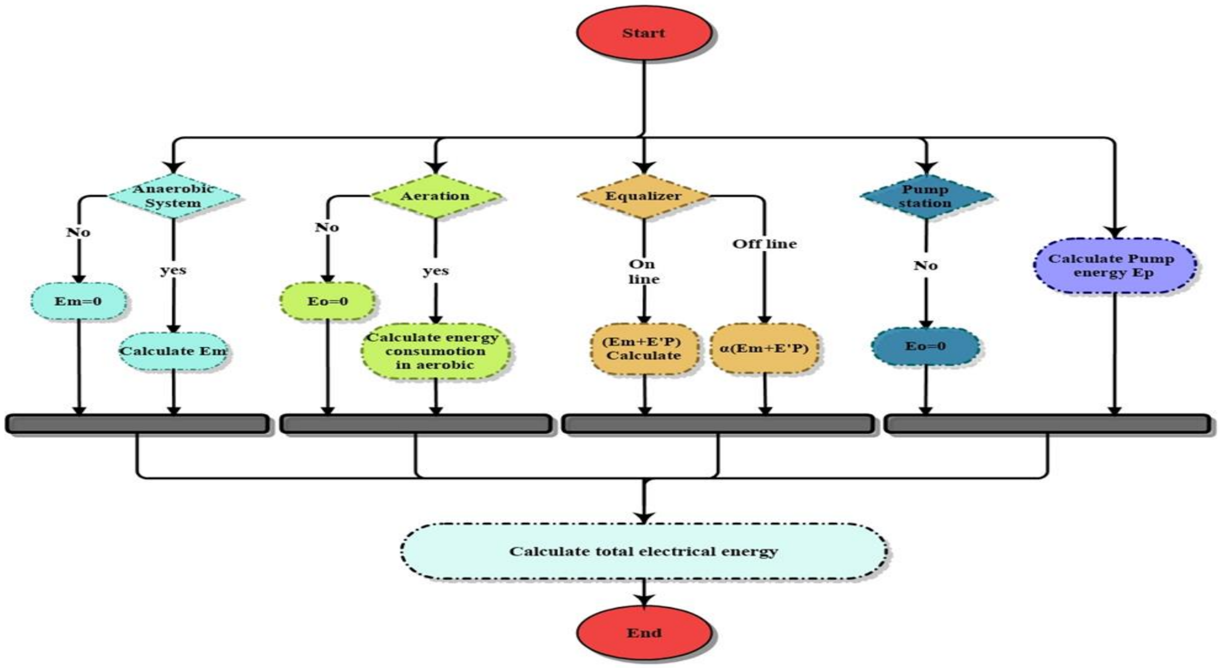


**Figure 1.** Energy activity diagram in an industrial wastewater treatment plant.

### 2.2.2. Developing ANNs model

A data set from AIP has been utilized to develop the ANN model. Six parameters, including BOD, COD, total nitrogen (TN), total phosphorus (TP), MLSS, and Q, were measured on a daily basis for four months. To ensure the quality and accuracy of the data, an outlier detection test was conducted on the tabulated data to eliminate potential erroneous or inconsistent inputs. This process ensured that the data used for the ANN model were error-free. These refined data were then implemented in the ANN model. Values of some descriptive statistics for these variables are shown in Table 2. The most important variables were defined through 1 to 4 models. Eventually, the best number of variables and the best model have been identified and involved in the simulation.

**Table 2**. Data for Amol IWWTP

| Variable | BOD (mg.L$^{1}$) | COD (mg.L$^{-1}$) | TN (mg.L$^{-1}$) | TP (mg.L$^{-1}$) | MLSS (mg.L$^{-1}$) | Q (m$^{3}$.day$^{-1}$) |
|---|---|---|---|---|---|---|
| Minimum | 1073 | 1459 | 9 | 3.3 | 1800 | 1000 |
| Maximum | 3079 | 4620 | 19.5 | 10.9 | 3800 | 1302 |
| Average | 1973 | 2786 | 13 | 7.7 | 2466 | 1122 |

In the process of developing the ANN model, the first step involves determining the number of neurons in the different layers. The input layer consists of six neurons, each corresponding to one of the key input parameters (BOD, COD, total nitrogen, total phosphorus, MLSS, and Q). These parameters were selected based on actual collected data and play a crucial role in predicting the model's performance.

The hidden layer, which is the most critical component for learning and generalizing the model, requires careful selection of the number of neurons to optimize the model for achieving the best performance and accuracy in predicting research outcomes. Hidden layers enable the network to generalize. Hypothetically, any continuous function can be simulated by a network with a hidden layer and an adequate number of hidden neurons, leading to a rich and flexible class of universal approximators (Dawson and Wilby, 2001; Fischer, 2006). The activation function employed in this layer plays a significant role in enhancing the model's learning capabilities and preventing issues such as network saturation, which directly impacts the quality of predictions. The output layer of the network consists of a single neuron that produces the predicted value for electrical energy consumption (EEC). A linear activation function is used in this layer to establish a direct relationship between the input parameters and the output, allowing for precise predictions of the final result. The second stage involved determining the learning rate, training algorithm, number of iterations, and training-stopping criteria. The number of epochs refers to the frequency with which the training data is presented to the network, helping the network learn from the patterns within the data. On the other hand, the training stopping criteria define the conditions under which training ceases, such as a lack of improvement in the model's performance over a specified period. These settings are key factors in preventing overfitting and optimizing the model's performance. In this study, a multi-layer perceptron network was generated according to the number of data and the structure of network layers.

Determination of the number of hidden neurons is of great importance, this can usually be achieved by a trial and error task in ANN modeling (Özesmi et al., 2006; Palani et al., 2008). It has been suggested by the Alyud research company (2003) that the N should be in the range of I/2 to 4I, where the I is the number of inputs.

In this paper, we assessed a range of neurons from 4 to 17. The partitioning scheme 70%-15%-15% was the optimum associated one (i.e., the proportions of the samples allocated to the training, cross-validation, and testing sets were 70%, 15%, and 15%, respectively).

### 2.3. Theoretical equations

To evaluate the performance of the ANN model, correlation coefficient (R), and root mean square error (RMSE) were assessed, and the accuracy of the model was determined according to these criteria (Ali Abdoli et al., 2012). The root mean squared error (RMSE) can be defined as shown in Equation 7;

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{i\,actual} - y_{i\,predicted}\right)^2 \qquad (7)$$

Where the output of the process is $y_{i\,actual}$, $y_{i\,predicted}$ is the i$^{th}$ output of the network corresponding to the $y_{i\,actual}$ and N is the total number of data points.

## 3. Results and Discussion

### 3.1. Calculation of electric energy consumed in the treatment plant in the traditional way

The highest amount of electric energy consumed in the treatment plants is spent on pumping, mixing, and aeration, based on the energy efficiency diagram in the wastewater treatment plants in AIP (Figure 1). The electrical energy consumed in the pumps and mixers of the plant is calculated using Equations 1 and 2, and the obtained results are illustrated in the following figures.

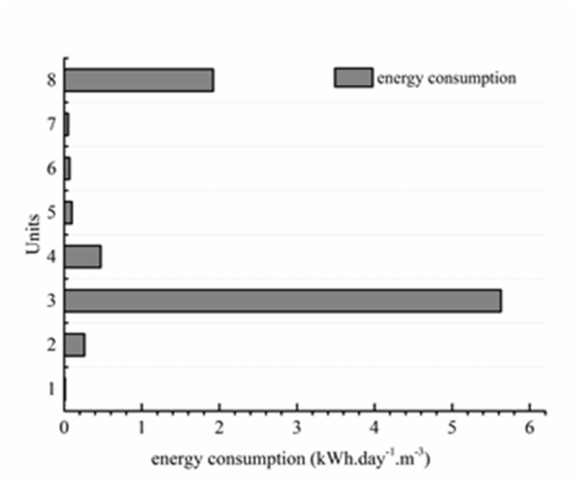


**Figure 2.** Electricity consumption of pumps and mixers

As shown in Fig. 2, the highest amount of energy is consumed in the aeration tank which is equal to 5.63 (kWh.day-1.m-3). The total amount of energy consumed by the pumps and the mixers was 2.88 (kWh.day-1.m-3). A large amount of this energy was spent on sludge filtration and in the filter press. The amount of energy consumed in the filter press was 1.92 kWh.day-1.m-3. The energy used in the aeration section is presented separately in the energy activity diagram and indicated by Eo (the electric energy consumption). To achieve this, the biological activity and substrate/food changes in the aeration tank were investigated and analyzed. The results are illustrated in Fig. 3.

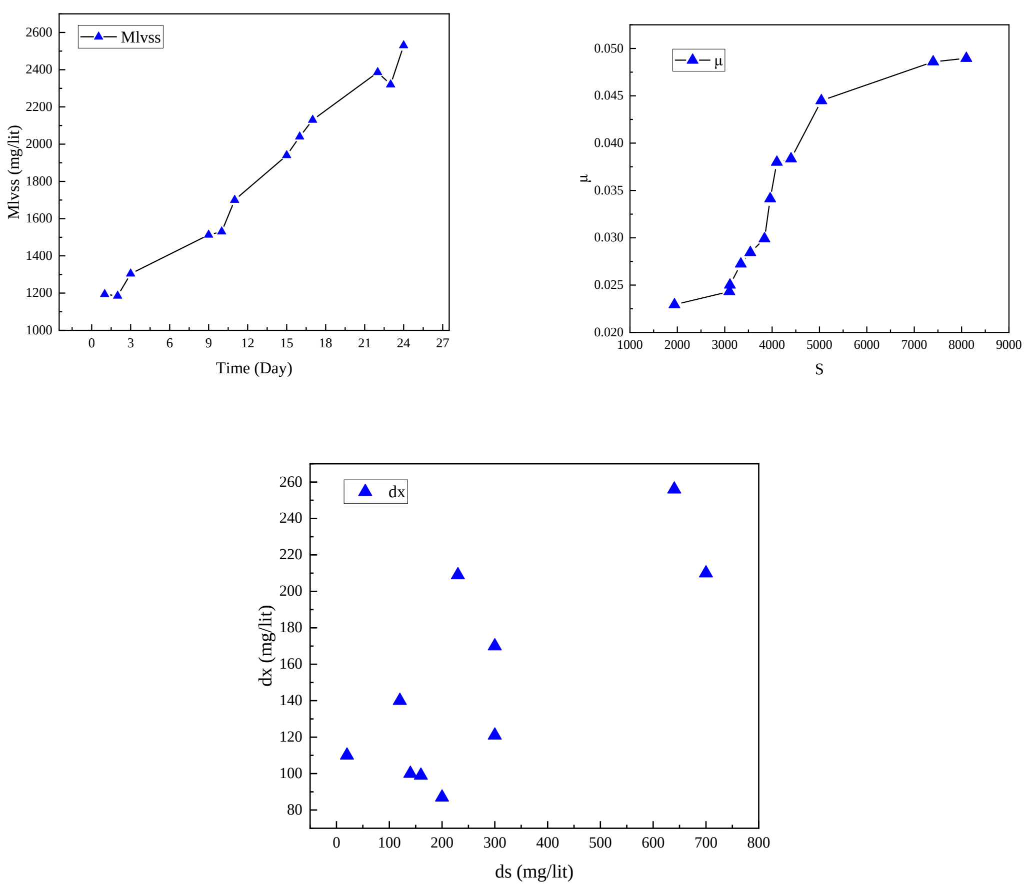


**Figure 3-a**. MLSS changes relative to time, b; the rate of biological growth in the aeration tank, c; biomass changes in relation to food changes

The amount of MLSS in the aeration tank was equal to the mass of living organisms (biomass). According to Figure 3-a, the fitted linear regression equation showing MLSS changes over time is as shown below.

$$MLSS = 58.02t + 1074 \quad (9)$$

The coefficient $R^2$ for the fitted linear regression equation is 0.98, which indicates the accuracy of the estimated equation. In addition, according to Figure 3-b, the biological growth rate is not the same at different concentrations of nutrients and the highest biological growth rate occurs at concentrations of 3000 to 6000 mg/L. The specific biological growth rate $\mu_{max}$ is 0.0489 and the $K_S$ is equal to 3108 mg/L as well. Finally, in Fig. 3-C, the changes of biomass production in the aeration with respect to the substrate changes are shown and the linear regression equation is presented, which is shown through Equation 10.

$$dx = 0.204ds + 92.85 \quad (10)$$

The mean efficiency coefficient (Y) in the aeration tank is illustrated by the fitted line slope. The mean value of Y is equal to 0.204. It is noteworthy that the R-value in the equation is a bit low but still in an acceptable range (approximately 0.8). The accuracy can be further increased by increasing the input data.

At this stage, with obtaining the amount of Y and having the amount of COD removal and the inlet flow, the amount of oxygen required for aeration was obtained through Equations 5 and 6. The results are shown in Figure 4.

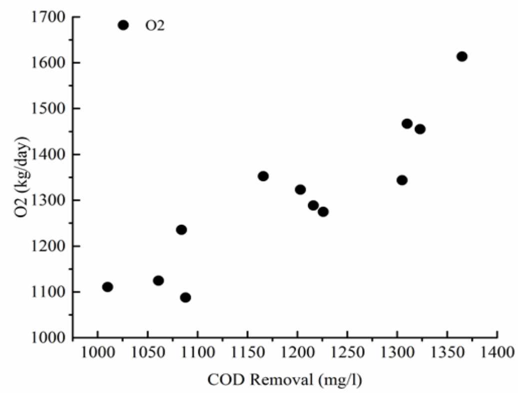


**Figure 4.** The amount of oxygen needed to consume carbon food

As shown in Figure 4, the amount of required oxygen in relation to COD removal had an upward trend so the amount of required oxygen increased with an increase in COD removal. The maximum amount of required oxygen has been 1614 (kg/day), which is used to remove 1365 mg/L of COD. Finally, by obtaining the required oxygen and having the consumed electrical energy, the linear regression equation was concluded to determine the amount of consumed electrical energy. In Figure 5, the amount of electrical energy consumed per oxygen requirement is illustrated.

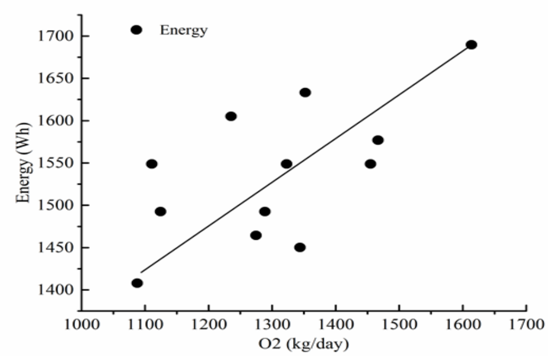


**Figure 5.** The amount of consumed electrical energy per required oxygen

The amount of electrical energy is fitted as a linear regression equation. The R-value in the equation is in an acceptable range and is approximately 0.8. The fitted linear equation is presented below.

$$Eo = 0.418O_2 + 1041 \quad (11)$$

Where $O_2$ is the amount of required oxygen to remove carbon (kg/day) and Eo is the electric energy consumption (wh). Therefore, with the help of the obtained equations, the required electrical energy (wh) can be obtained by having the amount of required oxygen. The electrical energy consumed in the aeration unit of treatment plants through energy consumption in aeration compressors was carried out by (Descoins et al., 2012) which is comparable to the results of the present study.

### 3.2.1. Developing ANN model

The main steps in developing ANN models are determining the appropriate input model, determining the type of network, partitioning and pre-processing the data, determining the network architecture; defining the performance criteria of the model, training, and validating the model (Falah Nezhad et al., 2016). hence, four neural network models, with different numbers of input parameters and neuron models were used to predict the electrical energy consumed by the treatment plant. Model 1 includes 6 variables, including BOD, COD, TN, TP, Q, MLSS, and 13 neurons in the intermediate layer. The amount of R and RMSE obtained in this model were accounted for 0.936 and 0.0068, respectively. Therefore, this model can be considered a suitable model for predicting electrical energy consumption. In Fig. 6, the results of actual values and values that were predicted by the neural network in Model 1, are illustrated. The actual values have been taken from the electricity bills of AIP.

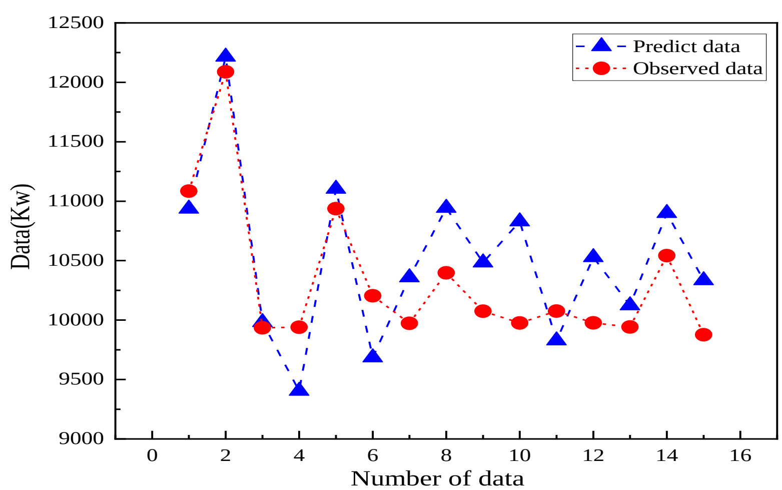


**Figure 6.** Real and predicted by model 1 electrical energy consumption.

The actual values of electrical energy consumed in the selected treatment plant have changed from 9876 to 12088 Wh, while the values predicted by model 1 vary from 9404 to 12215 Wh. The comparison between the obtained results shows both groups of data are in a close range. In addition, due to the high R-value and low RMSE in model 1, it can be concluded that this model has sufficient reliability to predict the amount of electrical energy consumption.

### 3.2.2. Sensitivity analysis

To assess the sensitivity of input parameters to the model, network error with all parameters was calculated. Then, some of the input parameters were eliminated to calculate the ratio of obtained error to the total error of the model. The higher ratio was equivalent to the more importance of the eliminated parameter and hence, we could consider the parameter in a higher rank compared to others. When the error ratio is less than one it shows the given parameter is not remarkably effective and could be eliminated from the model. The sensitivity results of input parameters in models 1 to 4 are shown in Table 3.

**Table 3.** Neural network models

| Model | Variables | neurons | Ratio |
|---|---|---|---|
| 1 | BOD, COD, TN, TP, Q, MLSS | 13 | 1 |
| 2 | COD, TN, TP, Q, MLSS | 13 | 1.28 |
| 3 | COD, TN, TP, Q | 13 | 3.1 |
| 4 | COD, MLSS, Q | 11 | 1.46 |

As shown in Table 3, in Model 1, six input variables were considered, including COD removal rate, BOD removal rate, nitrogen removal rate, phosphorus removal rate, inlet flow, and MLSS. The best result was obtained in the case with 6 input variables and 13 neurons in the intermediate layer, in which R and RMSE were equal to 0.936 and 0.68%.

In Model 2, the number of variables was reduced to 5, and one of the input variables (BOD) was eliminated. The results revealed that R and RMSE values in this model, which contains 13 neurons in the intermediate layer, accounted for 0.935 and 0.87%, respectively. It showed that the elimination of the BOD parameter had no significant effect on the results, and energy consumption was still accurately predicted which was due to the dependence of the COD and BOD parameters on each other. However, it should be noted that model 2 with five variables will be more efficient than model 1 with 6 input variables due to the lower number of variables.

In the next model (Model 3), the number of variables was reduced to 4, and the input variables included COD removal, nitrogen removal, phosphorus removal, and Q. The best result in this model was obtained when 4 input variables and 13 intermediate layers were employed. Measured R and RMSE for this mode were equal to 0.902 and 2.1%, respectively, and this model could not meet a high accuracy. Hence, it can be concluded that MLSS is an effective variable in the prediction of energy. This is because, with the elimination of this variable from input variables, the value of R dropped, therefore, this 4-variable model for prediction of electrical energy consumption in a treatment plant is not recommended.

In model 4, three input variables were considered. Since the previous models had shown that COD and MLSS parameters have a great influence on the determination of the electrical energy of the IWWTP, the nitrogen removal and the phosphorus removal parameters were eliminated in this model. The best result in this model was obtained with 11 neurons in the intermediate layer, in which R and RMSE were equal to 0.928 and 0.98%, respectively. The results revealed that model 4 has high accuracy in the prediction of energy consumption. In addition, it can be seen that the results of models with three and six input variables (containing nutrient removal) do not differ significantly, because the parameters of nitrogen and phosphorus removal, did not have a significant impact on the final results, mainly due to their exiguity and the low changes of range. Also, the dependence between the COD and BOD variables causes that removing one of them does not have a significant impact on the final result. Furthermore, when the number of input variables has changed from 6 to 3, the number of intermediate neurons has changed from 13 to 11 for the optimal answer because the number of neurons is directly related to the input variables.

Taking all the results, it can be concluded that parameters, such as COD, MLSS, and Q were of great importance compared to other available parameters and can be considered to be the fundamental required parameters to predict the amount of electrical energy. In addition, model 4 is accurate enough to predict the amount of electrical energy. Figure 7 illustrates the actual and predicted values obtained by the neural network via model 4.

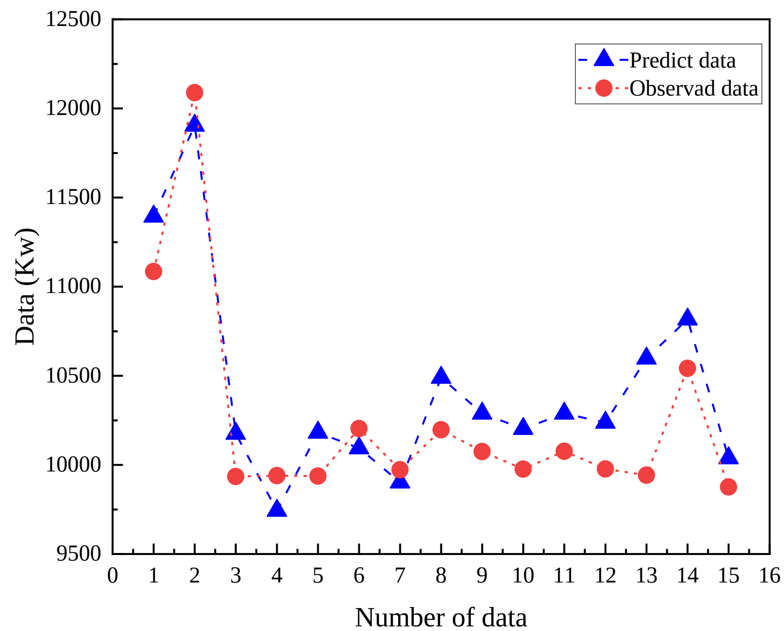


**Figure 7.** Real and predicted electric energy consumption by Model 4

The actual values of electrical energy consumption in the selected treatment plant changed from 9876 to 12088 Wh, and the values predicted by model 4 vary from 9744 to 11904 Wh, which was in an appropriate range.

In the study by Maged et al., ANN models were developed to predict the performance of a wastewater treatment plant. The data used were collected from a major treatment plant in Greater Cairo, Egypt. The dataset included daily records of BOD and SS concentrations across various stages of the treatment process over a 10-month period. The results demonstrated the high capability of ANN models in accurately predicting the performance of the treatment plant (Hamed et al., 2004). In the study by Wang et al., which includes two wastewater treatment plants located in Chongqing, China, artificial neural networks ANNs were used to predict electrical energy consumption in wastewater treatment plants. The results showed that these models were able to predict energy consumption with high accuracy and help optimize energy use in the treatment processes (Wang et al., 2022). In our study, the application of artificial neural networks to predict electrical energy consumption in IWWPT was also investigated. The results indicated that these models provide high accuracy and optimal performance in energy prediction and can serve as an efficient tool for energy management in treatment plants.

## 4. Conclusions

Nowadays, due to the shortage of energy resources, the rising cost of energy, environmental problems, and problems associated with high energy consumption, such as global warming, energy consumption management has been the subject of significant attention. In this study, the energy consumption of IWWTP was investigated by employing a traditional method as well as a neural network. According to the given process, the determination of energy consumption in the traditional method demands a lot of time and energy to collect and analyze information and it may be affected by human/equipment errors. Hence, finding an accurate and efficient method to predict energy consumption is absolutely necessary. The neural network provides a very powerful tool for predicting the amount of energy consumed in industrial wastewater treatment plants. To model the energy consumption in the neural network, model 1 with six input variables was first used, and then further models were considered to assess the sensitivity of the model and to determine the impact of each of the selected input parameters on the result. According to the results of all neural network models, and given the higher importance of some of the input variable parameters, the optimal model structure in predicting the electrical energy consumption of the AIP was chosen which is a neural network with three input variables, including COD removal, MLSS, and inlet flow, with 11 neurons in the intermediate layer and the (Levenberg-Marquardt training algorithm) LM training function. Considering the impact of indicators on the obtained results from each model, and the fact that the best solution with the least variable parameters would be the most favorable design conditions in the neural network, model 4 was chosen as the best model, which indicates the high accuracy of this neural network model in predicting the electrical energy consumption rate by IWWTP. Considering the promising results of this study, future work could focus on developing hybrid models combining neural networks with optimization algorithms, expanding input parameters for deeper analysis, and implementing the model in other industrial settings. Additionally, long-term energy consumption prediction, economic and environmental impact assessment, and real-world operational testing could further enhance the model's applicability and efficiency.

## List of abbreviations

| Abbreviations | Definition |
|---|---|
| AIP | Amol’s industrial park |
| ANN | Artificial Neural Network |
| BOD | Biological Oxygen Demand |
| BPNN | Back Propagation Neural Network |
| COD | Chemical Oxygen Demand |
| CG | Conjugate Gradient |
| EEC | Electrical Energy Consumption |
| MLP | Multilayer Perceptron |
| IFAS | Integrated Fixed Bed Activated Sludge |
| IWWTP | Industrial Wastewater Treatment Plants |
| MLSS | Mixer-mixed liquor suspended solids |
| TN | Total Nitrogen |
| TP | Total Phosphorus |
| UAPB | Upflow Anaerobic Packed Bioreactor |
| UAFB | Upflow Anaerobic Fixed Bed |

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