



Modeling of Tehran South Water Treatment Plant Using Neural Network and Fuzzy Logic Considering Effluent and Sludge Parameters

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Abstract:

The disposal of sewage with acceptable qualitative characteristics to different acceptor resources is an environmental issue that today's societies face (with). Using the MatLab software, a neural network model, and an adaptive neuro-fuzzy inference system (ANFIS), this study has predicted the qualitative parameters (COD, BOD₅, and TSS of the wastewater, along with TS, VS, and SOUR of the sludge) for the south Tehran sewage treatment plant and finally chosen the best models by validating the model and using the defined criteria. Moreover, using these developed models and comparing their results with the available standard values provides a suitable classification to reuse the wastewater and sludge of the south Tehran wastewater treatment plant. The results indicated acceptable errors of both systems, the adaptive neuro-fuzzy inference system and the artificial neural network, in predicting the qualitative characteristics of the sludge and wastewater of the south Tehran sewage treatment plant and the priority of the adaptive neuro-fuzzy inference system over the artificial neural network in estimating the quality of the treated wastewater and sludge.

1. Introduction

When talking about sewage and its treatment, the issue of the environment and its protection from pollution is among the subjects that come to mind, since sewage is always considered a polluting resource in the human and natural environment [1]. The main goals of construing sewage treatment plants include preserving public health, protecting the environment, preventing the pollution of water resources, and reusing the treated wastewater in agriculture and industry [1-3].

With the increased population growth and extended range of human activities in different aspects, the water consumption per capita has significantly raised over the past century. In such conditions, using unconventional water resources, such as the wastewater of sewage treatment plants in different sectors, especially agriculture, which makes up the major portion of water consumption, is of great importance. Today,

the use of wastewater in agriculture is common in many countries of the world, including the United States, Canada, France, Germany, Brazil, Egypt, Morocco, Jordan, Saudi Arabia, Qatar, and China [4-7].

Iran is located in an arid and semi-arid climate, and a report by the World Bank has predicted that the country's water scarcity will worsen and even become twice as much by 2025 if the existing climate persists [8]. Thus, using treated water is of great importance in the country. Furthermore, accurately leading the sewage treatment plants is a key factor in managing the water and sewage sector. On the other hand, according to the statistics, the volume of unconventional water, such as urban and industrial wastewater, used in Iran in 1996 was almost 3.4 billion m³, 2.5 billion m³ of which was urban wastewater [9]. Given the growth of civilization, the volume of wastewater has remarkably increased. Therefore, properly leading the sewage treatment plants is among the key factors in managing the water and sewage sector [10].

The performance of sewage treatment plants incorporates a function of various qualitative factors of the sewage, management conditions of the plant, and environmental issues. The disposal of sewage with acceptable qualitative

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characteristics to different acceptor resources is an environmental issue that today's societies face. Sewage treatment plants include numerous complex physical, biological, and chemical processes. Most of these processes show nonlinear behaviors, which cannot be easily described by linear mathematical models [11].

With respect to the mentioned points, employing methods that can predict the performance and efficiency of sewage treatment plants, especially based on the quantitative and qualitative variations in the entered sewage procedure conditions or climatic conditions, is of crucial importance. Based on these predictions, an operator can take the required measures before the problems occur, and thus, apply a proper control and operation. Furthermore, making decisions promptly and implementing them using the predicted results of the used model can save time and cost. This study aims to employ the neural network model and fuzzy logic to predict the intended qualitative parameters of the sewage treated in the south Tehran sewage treatment plant as a case study, use the obtained wastewater, and finally classify the quality of the treated sewage and sludge. According to the points stated, this model can be suitable for improving the sewage treatment plant's efficiency.

2. Literature review

Over recent years, numerous studies have been conducted on modeling in the water and sewage field throughout the world. These studies include the use of artificial intelligence models, such as artificial neural networks and adaptive neuro fuzzy inference systems for estimating the quantitative and qualitative parameters of different rivers in the world, the use of modeling to estimate the surface area and qualitative parameters of groundwater resources, quantitative and qualitative estimation of the returned sludge required in the sewage treatment plants, estimation of the qualitative parameters of the water and sewage entering the water and sewage treatment plants, and many other usages [12-39].

Shokri et al. [40] proposed two fuzzy models, namely Sugeno and Mamdani, to evaluate the sewage treatment plant of Tabriz, and obtained the correlation coefficients of 0.91 and 0.94 for the parameters BOD₅ and TSS, respectively. The results showed that both developed models could properly validate the performance of the sewage treatment plant. Using the partial least squares regression (PLSR) and perceptron neural network, Modarresi and Mirbagheri [41] modeled the sludge volumetric index (SVI), an important parameter of active sludge treatment plants, for the treatment plant of Shahrak-e Qods. Using the five input data of MLSS, BOD₅, T, pH, and MLVSS, and the output data of SVI, they achieved the correlation coefficients of 0.352 and 0.836 using the R program and the artificial neural network, respectively, and found that the artificial neural network provided better results compared to the

PLSR model. Using the statistics of a four-year period, the sewage input data, including Q, BOD₅, COD, pH, T, TSS, and DO, and output sewage parameters of BOD₅, TSS, and pH, Rafat Motavalli et al. [42] compared the capability of an ordinary artificial neural network and an artificial neural network optimized with the genetic algorithm to simulate the semi-mechanical sewage treatment plant (aerated lagoon) number 1 of Mashhad. The parameter BOD₅ obtained a correlation coefficient of 0.86 and a root-mean-square error (RMSE) of 14% in the ordinary artificial neural network, and a correlation coefficient of 0.93 and a root-mean-square error (RMSE) of 10% in the one optimized by the genetic algorithm. Dacewics [43] discussed the use of Decision Support Systems (artificial neural networks analysis preceded by Principal Component Analysis) for the assessment of domestic sewage filtration effectiveness with four types of waste serving as filling materials in vertical flow filters. He presented good agreement between the predictions of the neural model and the reduction values was obtained for the MLP 11-7-2 network. Pisa et al. [44] proposed a new control approach based on Internal Model Controllers (IMC) adopting Artificial Neural Networks (ANNs), which are able to model the real plant behaviour without performing linearisation. Their results show that the proposed IMC is improving the default controller performance around a 16% and a 53% in terms of the Integral Absolute Error (IAE) and the Integral Square Error (ISE), respectively. Yogeswari et al., [45] used an artificial neural network (ANN) to estimate the hydrogen production from confectionery wastewater. The modelling was performed using the input parameters like time, influent chemical oxygen demand (COD), effluent pH and volatile fatty acids (VFA). The result of the tested data for hydrogen production rate was successful. The calculated average percentage error (APE) for hydrogen production rate was 0.0004. Godini et al., [2] modeled an industrial aerated lagoon system in terms of the operating parameters by use of a neuro-evolutionary approach, combining differential evolution (DE) algorithm and artificial neural networks (ANN). The mean squared error of the best solutions were in the order of 10⁻⁴, illustrating the effectiveness and reliability of the developed models.

Pai et al. [46] employed three adaptive neuro-fuzzy inference systems (ANFIS) and an artificial neural network model to predict the SS and COD of the sewage coming out of a hospital treatment plant. The correlation coefficients of 75% and 92% and root-mean-square errors (RMSE) of 0.41 and 4.42 were respectively obtained for the mentioned parameters by the best ANFIS, showing its higher efficiency compared to the artificial neural network model with correlation coefficients of 71% and 82% and root-mean-square errors (RMSE) of 0.53 and 6.10. Using the Mamdani fuzzy inference system, Yel and Yalpir [47] succeeded in predicting the qualitative factors of the wastewater resulting from urban treatment plants in Turkey. They used the

indexes of T, pH, COD, BOD, and SS of the sewage as the inputs of the Mamdani fuzzy inference system to predict the pH, COD, and SS of the wastewater. The obtained results indicated proper efficiency of the used fuzzy systems with minimum absolute errors of 4%, 7%, 11%, and 9% for the COD, pH, BOD, and SS, respectively. The capability of the artificial neural network and fuzzy logic in modeling the qualitative characteristics of the sewage treatment plant of a paper factory in China was evaluated by Wan et al. [48]. Their findings indicated root-mean-square errors (RMSE) of 1.135% and 0.184% for predicting the COD and SS, approving the high capability of the used models in the issues associated with treatment plants. In another study, Pai et al. [49] employed three types of adaptive neuro-fuzzy inference systems (ANFIS) to predict the COD, SS, and pH of the sewage that came out of an industrial treatment plant and compared them with those obtained from an artificial neural network model. The correlation coefficients of 0.96, 0.93, and 0.95 and root-mean-square errors (RMSE) of 0.43, 1.48, and 0.04 were respectively obtained for the mentioned parameters by the ANFIS, showing its higher efficiency compared to the artificial neural network model with correlation coefficients of 0.89, 0.83, and 0.93 and root-mean-square errors (RMSE) of 0.71, 0.47, and 0.05. Belhaj et al. [50] modeled the behavior of the Sfax sewage treatment plant in southeastern Tunisia using a linear multivariable regression model. Having the sewage parameters, including TKN, BOD₅, COD, pH, T, SS, and FC, from 2008 to 2010, they could model the treatment plant with good approximation, obtaining the coefficients of determination of 0.973, 0.946, and 0.925 for the treated sewage parameters of COD, BOD₅, and SS.

3. Reusing the wastewater and sludge obtained from the sewage treatment

Various aspects, including hygienic, economic, social, cultural, managerial, and environmental ones, are considered in using the wastewater obtained from the wastewater treatment. In order to use the wastewater, these aspects should be evaluated prior to planning. Therefore, many urban societies believe that the treated sewage should reach acceptable standards to allow for reusing the wastewater in different conditions [51].

The use of raw and untreated sewage has been common in different countries for a long time. Since the mid-1900s and the beginning of microbial pollution in surface water resources of industrial countries (especially in Europe and the United States) which caused extensive hygienic problems, sewage treatment plants have been gradually developed in urban areas. In developed countries, only the treated sewage is used according to the related requirements and standards. The industrial and population growth has been at such a level that in most developing countries, the existing treatment plants do not suffice for the produced sewage and wastewater, and in some areas, raw and polluted

wastewater is consumed for different uses, resulting in undesirable hygienic and environmental consequences. The lands irrigated with sewage and wastewater are estimated to be more than 2.5 million hectares, making up almost 1% of the water agricultural lands [52].

Despite the past background of using wastewater in the country, studies in this field began three decades ago. In some of these studies, the main focus is on the environmental effects of using such resources, and some other studies have investigated the effect of this water on the quantity and quality of products. For example, three wastewater transmission plants have been launched for the irrigation of green space in Isfahan, through which the wastewater of the north, east, and Shahinshahr sewage treatment plants is used for the green belt and urban afforestation in the east of Isfahan [53].

Today, given the increasing population growth, especially in large cities, and the need for qualitative protection of water resources and the environment, the sludge management of water treatment plants is of great importance. The disposal of sludge is considered among the fundamental problems in the sludge management of water treatment plants. The great volume of the produced sludge and the undesirable characteristics of impounding are among the main reasons behind this problem. Therefore, the optimum method for disposal and reuse of sludge should be chosen according to the environmental issues and economic conditions. Currently, no regulations have been imposed on the disposal of sludge in Iran to provide particular instructions. Meanwhile, in developed countries, what remains of the consumed water is considered as dangerous waste material which is recycled using other processes in the best possible form, and disposal is considered as the last alternative [55].

4. Research methodology

In order to measure the quality of wastewater and evaluate the sewage treatment plants, the parameters of temperature, BOD₅, COD, TSS, and pH are measured and recorded in the outlet of the plant and compared with the corresponding values in its inlet. The BOD₅, COD, and TSS are among the most important indexes to evaluate the pollution level of sewage and compare it with different standards to reuse it or discharge it into water resources. On the other hand, successful environmental management requires the continuous performance monitoring of different sewage treatment systems and effort and planning to improve their efficiency. In this research, the required data were obtained from the south Tehran sewage treatment plant. Using the MatLab software, a neural network model, and an adaptive neuro-fuzzy inference system (ANFIS), the qualitative parameters (COD, BOD₅, and TSS of the wastewater, along with TS, VS, and SOUR of the sludge) of the treated sewage were predicted and, finally, the best models were chosen by validating the model and using the defined criteria.

4.1 Artificial neural network

The artificial neural network is, in fact, a simplified model of the human brain. This network is a mathematical structure capable of showing the arbitrary nonlinear processes and combinations to connect the inputs and outputs of any system. Using the available data, this network is trained and used for a prediction about the future. The neural network is made up of neural cells called neurons and communication units called axons. The neurons of the artificial neural network are a very simple form of biological neurons. Despite having higher speed, the artificial neural networks made up of these neurons have lower ability compared to the biological ones. Fig. 1 demonstrates a simple view of an artificial neural network.

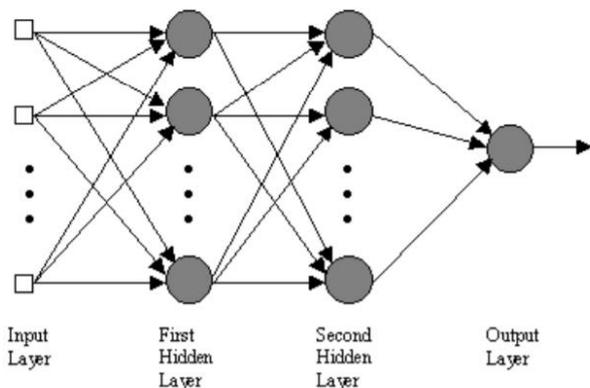


Fig. 1: A simple view of the artificial neural network model

According to Fig. 1, each artificial neural network consists of three layers: an input layer, an output layer, and a hidden layer. On each of these layers, there are a number of neurons which act as processing units and are related to each other through weighted connections. The operations performed in each neuron are as the following:

1. The neuron adds together the whole data that has reached the cell.
2. The obtained amount is compared with a threshold
3. Transmit the data followed by the result through an activation function
4. Finally, the neuron's output is obtained.

By employing some procedures, the error is minimized. The activation functions, such as sigmoid, linear, and threshold functions, are used to transfer the outputs of each layer to the next layers. The parameters effective in the artificial neural network are as follows:

- A suitable training level: An important criterion in training a network is the number of epochs the network experiences while training, which is critical to be properly determined. In general, as the number of epochs in training the network increases, lower training error occurs in it. However, when the number of epochs exceeds a particular value, the

error of the test set network training also increases [55].

- The number of layers in the network: It is among the main criteria in designing neural networks. These networks are usually comprised of several layers (Fig. 2). An input layer acts as a buffer and makes no change in the input signal. Therefore, it is ignored when counting the number of layers. A network includes an output layer that is the ultimate output of the network and provides its response to the input signals. The remaining layers located between the input and output layers are called middle layers, whose number is determined by trial and error.

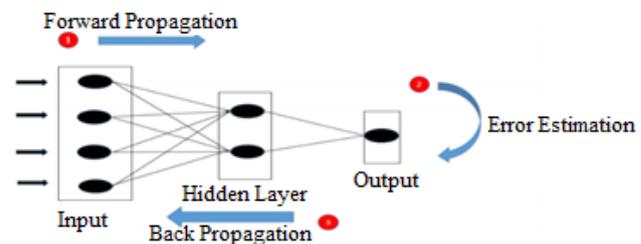


Fig. 2: The schematic of the artificial neural networks

- Activation functions: The internal mode of a neuron caused by the activation function is known as the activity level. Generally, each neuron sends its activity level to one or more other neurons in the form of a single signal. The activation functions of a layer's neurons are usually, but not essentially, the same. Moreover, these functions are nonlinear for the neurons of the hidden layer while being identity functions for the input layer's neurons. Using a reaction function, a neuron produces outputs for various inputs. The linear and sigmoid functions are the two well-known functions [56].
- Training rules: The training functions are among the main parameters in neural networks. Various training functions are used to train a network.

4.2 Fuzzy inference system

The fuzzy set is an almost new mathematical theory proposed by the Iranian scientist, professor Lotfi Asgharzadeh [57]. This theory aims to find mathematical patterns that are compatible with human thinking and inference, as well as natural and real patterns. Although this branch of science is very underdeveloped, remarkable advances have been made from both theoretical and practical aspects. The fuzzy set A from the reference set X is a set whose members are the elements of the X , each with a degree between zero and one. A function that indicates the membership degree of each member of X in A is called the membership function of A in X . As the membership degree of an element (x) is closer to one, x has more connection to

the fuzzy set A, while degrees close to zero demonstrate lower connection of the x to it [57].

The fuzzy inference system is based on if-then rules which are used to obtain the relationship between a number of input and output variables. Therefore, the FIS can be used as a predicting model for conditions in which the input or output data have high uncertainty since, in such conditions, the classic prediction methods like regression cannot properly consider the uncertainties existing in the data. Generally, the steps of a fuzzy inference system can be expressed as the following [58]:

- Determining a fuzzy rule-based system based on observational data
- Defuzzification of the antecedent and consequent parts using the fuzzy membership function
- Combining different parts of the antecedent part of each of the rules and consequently determining its intensity and effect on the final output of the system
- Combining the consequent part of the rules to obtain the final output of the system in the form of a fuzzy set
- Converting the final output of the system to a classic number using Defuzzification techniques

4.2.1 Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive neuro-fuzzy inference system is properly capable of training, development, and classification, while having the advantage to allow for the extraction of fuzzy rules from the numerical information or expert knowledge, and adaptively develop a rule-based system. Furthermore, it can regulate the complex conversion of human intelligence to fuzzy systems. The major problem of the ANFIS prediction model is that it requires considerable time to train the structure and determine the parameters. The distinctive characteristic of the ANFIS is the provision of the hybrid learning algorithm of the back-propagation and least-squares methods to modify the parameters. The back-propagation gradient based method is employed to regulate the antecedent nonlinear parameters, while the least-squares method is used to determine the linear parameters of the consequent part. The training procedure includes two steps. In the first step, assuming constant values for the antecedent parameters, the least-squares method is used to determine the consequent parameters. In the second step, the error signals are backpropagated. The back-propagation method is used to modify the antecedent parameters by minimizing the total second-order cost function [59].

4.3 South Tehran sewage treatment plant

The south Tehran sewage treatment plant (Fig. 3), including eight units and covering 4.2 million people, has been constructed to treat a portion of the sewage collected from the city of Tehran. The average entering sewage capacity of units 1-4 is predicted 450000 m³ per day. The plant has an area of 110 hectares located in the southwest of Shahr-e-

Rey. This project has been implemented to treat the sewage produced by 2.1 million people, occupying 31 hectares of the plant land. The sewage is treated using the activated sludge process and nitrogen removal. The obtained wastewater is transferred to the irrigation network of Varamin plain and used to irrigate almost 50000 hectares of the land. The sludge produced in the plant can also be used as a fertilizer in 6000 hectares of agricultural land.



Fig. 3: South Tehran sewage treatment plant

4.4 Modelling Steps and Details

The data required for this study were obtained from the south Tehran sewage treatment plant. Using the MatLab software, a neural network model, and an adaptive neuro-fuzzy inference system (ANFIS), the qualitative parameters (COD, BOD₅, and TSS of the wastewater, along with TS, VS, and SOUR of the sludge) of the treated sewage were predicted and, finally, the best models were chosen by validating the model and using the defined criteria.

Thus, by using the developed models and comparing their results with the standard values shown in Table 1 for different wastewater uses, a proper classification can be provided to reuse the wastewater of the south Tehran sewage treatment plant. The qualitative properties of the sludge produced in the plant should be as the following to ensure no odor emission and proper moisture content to use them:

The ratio of volatile solids to total solids should be lower than 0.57 ($VS/TS < 0.57$).

The specific oxygen uptake rate (SOUR) should be lower than 1.5 mgr O₂ per gr of solids ($SOUR < 1.5$).

The total solids in the buried sludge should be lower than 25% ($TS \geq 0.25$).

Table 1: The discharged wastewater standards of the Department of Environment

| Index | Discharge into surface water (mg/l) | Discharge into absorbing well (mg/l) | Agriculture and irrigation use (mg/l) |
|------------------|-------------------------------------|--------------------------------------|---------------------------------------|
| BOD ₅ | 30 | 30 | 100 |
| COD | 60 | 60 | 200 |
| TSS | 40 | - | 100 |

4.4.1 Data preparation

Of the collected data, 75% were used for training, and 25% were used for validation of the neural and adaptive neuro-fuzzy models. Since introducing the raw data reduces the speed and accuracy of neural models, the data were normalized. The normalization prevents the excess reduction in the weights and early saturation of the neurons. In this process, each datum is converted to a number within zero and one.

$$X_{normal} = 0.05 + (0.95 \times (X - X_{min} / X_{max} - X_{min})) \quad (1)$$

4.4.2 Artificial neural network in Matlab

The Neural Network toolbox in the MatLab software was used for modeling with the artificial neural network. The training and activation functions used in the model included the Resilient, Bayesian Regularization, Levenberg-Marquart, Scaled Conjugate Gradia, Backpropagation, and BFGS Quasi-Newton as training functions and logsig, purelin, and tansig as activation functions. The network's performance was based on variations in the training and activation functions, variations in the number of middle layers, and a maximum iteration number of 1000. For various networks employed in this study, five or six neurons were used in the input layer, six to twenty neurons were used in the middle layer, and one neuron was used in the output layer. It is natural that with the rise in the number of neurons in the input layer, i.e., the number of input variables in the models, for both training and validation stages, the coefficient of determination increases while the root-mean-square error is reduced. Fig. 4 illustrates a structure of the performance and relationship between the layers in the artificial neural network.

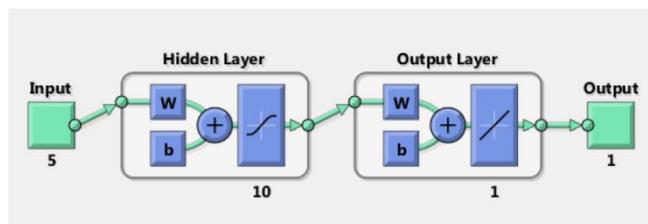


Fig. 4: A schematic of the artificial neural network model

4.4.3 Fuzzy inference system in Matlab

The Neuro-Fuzzy Design toolbox in the MatLab software was used for modeling with the adaptive neuro-fuzzy inference system (ANFIS). The trapmf, trimf, gbellmf, gaussmf, Gauss2mf, pimf, dsigmf, and psigmf were used as input membership functions while the constant and linear functions were used as the output membership functions. The backprop optimization method, an error tolerance of zero, and an iteration number of 30 were used in the models. Fig. 5 demonstrates a structure of the performance and relationship between the layers in the adaptive neuro-fuzzy inference system.

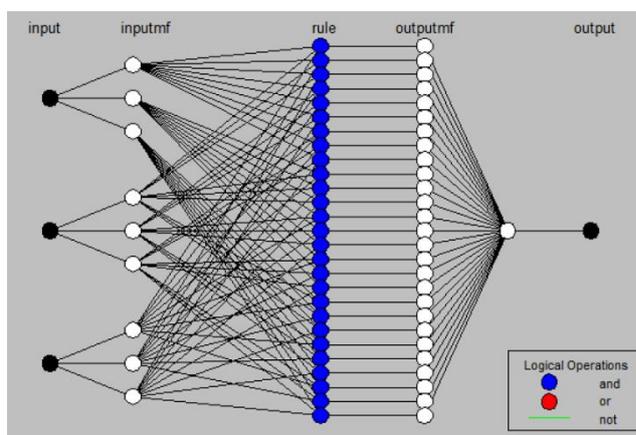


Fig. 5: A schematic of the adaptive neuro-fuzzy inference system (ANFIS)

4.4.4 Selection of the best model

The coefficient of determination and root-mean-square error calculated using Eqs. 2 and 3, respectively, were used to compare the developed models and choose the best one in estimating the qualitative values of the plant output. In these equations, T_i is the observational values, Q_i is the values calculated by the model, and N is the number of the data.

$$R^2 = 1 - \left[\frac{\sum_{i=1}^N (T_i - O_i)^2}{\sum_{i=1}^N T_i^2} \right] \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (T_i - O_i)^2} \quad (3)$$

Table 2: The discharged wastewater standards of the Department of Environment

| Model type | Model name | Training rule of the neural network/ input membership function of the ANFIS | Activation function of the neural network/ output membership function of the ANFIS | Structure of the neural network | Coefficient of determination | | Root-mean-square error | |
|-----------------|------------------|--|---|---------------------------------|------------------------------|------------|------------------------|------------|
| | | | | | Training | Validation | Training | Validation |
| Neural, daily | BA ₁₁ | Levenberg-Marquart | tansig | 1, 16, and 6 | 0.95 | 0.82 | 0.0110 | 0.0131 |
| Neural, monthly | BA ₁₅ | Levenberg-Marquart | tansig | 1, 20, and 6 | 0.85 | 0.77 | 0.0308 | 0.0462 |
| ANFIS, daily | BF ₁₀ | trapmf | linear | - | 0.97 | 0.88 | 0.0084 | 0.0100 |
| ANFIS, monthly | BF ₁₁ | gbellmf | linear | - | 0.92 | 0.87 | 0.0175 | 0.0211 |

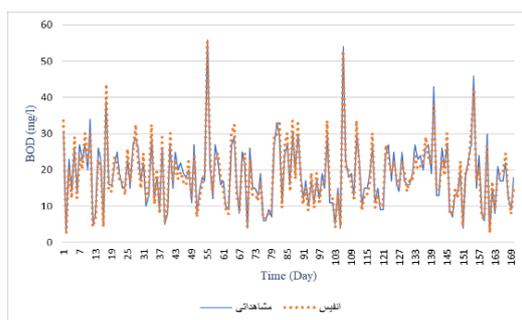
5. Results

5.1 Modeling the BOD₅ of the effluent of the sewage treatment plant

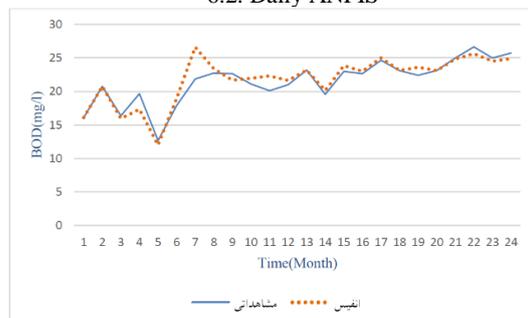
Given the reviewed studies and the collected data, the DO, COD, BOD₅, SVI, EC, and turbidity of the input sewage were used to model the BOD₅ of the output effluent in both neural network and the adaptive neuro-fuzzy inference system (ANFIS). Table 2 lists the results of the best daily and monthly models of the artificial neural network and adaptive neuro-fuzzy inference system (ANFIS).

The results of the model BA₁₁, which included the Levenberg-Marquart training function and tansig activation function, indicate that the artificial neural network could properly estimate the daily BOD₅ for the south Tehran sewage treatment plant. The structure of the BF₁₀ with the

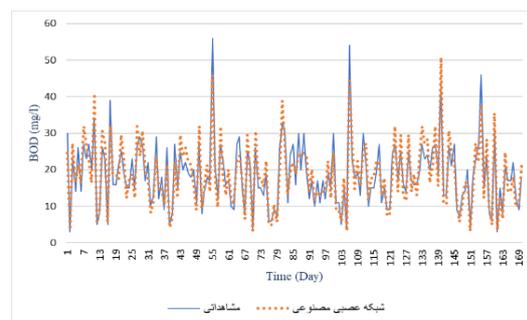
trapmf input membership function and linear output membership function shows the advantage of the adaptive neuro-fuzzy inference system over the neural network in daily models. The model BA₁₅ with the Levenberg-Marquart training function and tansig activation function (similar to the daily model) was able to properly estimate the monthly BOD₅ for the south Tehran sewage treatment plant while having a weaker performance compared to the daily neural model. The structure BF₁₁ with the gbellmf input membership function and linear output membership function was prior to the monthly neural network while showing weaker results compared to the daily ANFIS model. Fig. 6 provides the validation results of the best mentioned models.



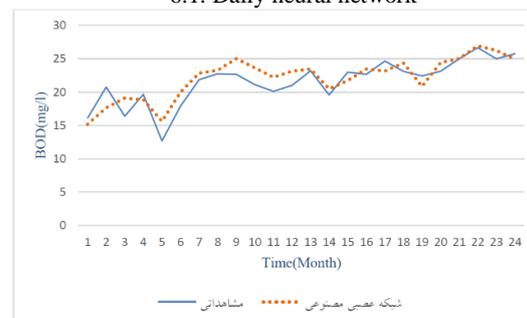
6.2. Daily ANFIS



6.4. Monthly ANFIS



6.1. Daily neural network



6.3. Monthly neural network

Fig. 6: Comparison of the output BOD₅ values of the best models with the observational values in the validation stage

Table 3: The results of the best daily and monthly TSS models

| Model type | Model name | Training rule of the neural network/ input membership function of the ANFIS | Activation function of the neural network/ output membership function of the ANFIS | Structure of the neural network | Coefficient of determination | | Root-mean-square error | |
|-----------------|------------------|--|---|---------------------------------|------------------------------|------------|------------------------|------------|
| | | | | | Training | Validation | Training | Validation |
| Neural, daily | TA ₆ | Levenberg-Marquart | tansig | 1, 11, and 5 | 0.88 | 0.81 | 0.0233 | 0.0299 |
| Neural, monthly | TA ₅ | Levenberg-Marquart | tansig | 1, 10, and 5 | 0.88 | 0.83 | 0.0308 | 0.0342 |
| ANFIS, daily | TA ₉ | trimf | linear | - | 0.92 | 0.84 | 0.0252 | 0.0265 |
| ANFIS, monthly | TF ₁₁ | gbellmf | linear | - | 0.90 | 0.88 | 0.0279 | 0.0307 |

5.2 Modeling the TSS of the effluent of the sewage treatment plant

Given the reviewed studies and the collected data, the EC, SVI, COD, TSS, and turbidity of the input sewage were used to model the TSS of the output effluent in both neural network and the adaptive neuro-fuzzy inference system (ANFIS). Table 3 lists the results of the best daily and monthly models of the artificial neural network and adaptive neuro-fuzzy inference system (ANFIS).

The results of the model TA₆, which included the Levenberg-Marquart training function and tansig activation function, indicate that the artificial neural network could properly estimate the daily TSS for the south Tehran sewage treatment plant. The structure of the TF₉ with the trapmf

input membership function and linear output membership function shows the advantage of the adaptive neuro-fuzzy inference system over the neural network in daily models. The model TA₅ with the Levenberg-Marquart training function and tansig activation function (similar to the daily model) was able to properly estimate the monthly TSS for the south Tehran sewage treatment plant while having a weaker performance compared to the daily neural model. The structure TF₁₁ with the gbellmf input membership function and linear output membership function was prior to the monthly neural network while showing weaker results compared to the daily ANFIS model. Fig. 7 provides the validation results of the best mentioned models.

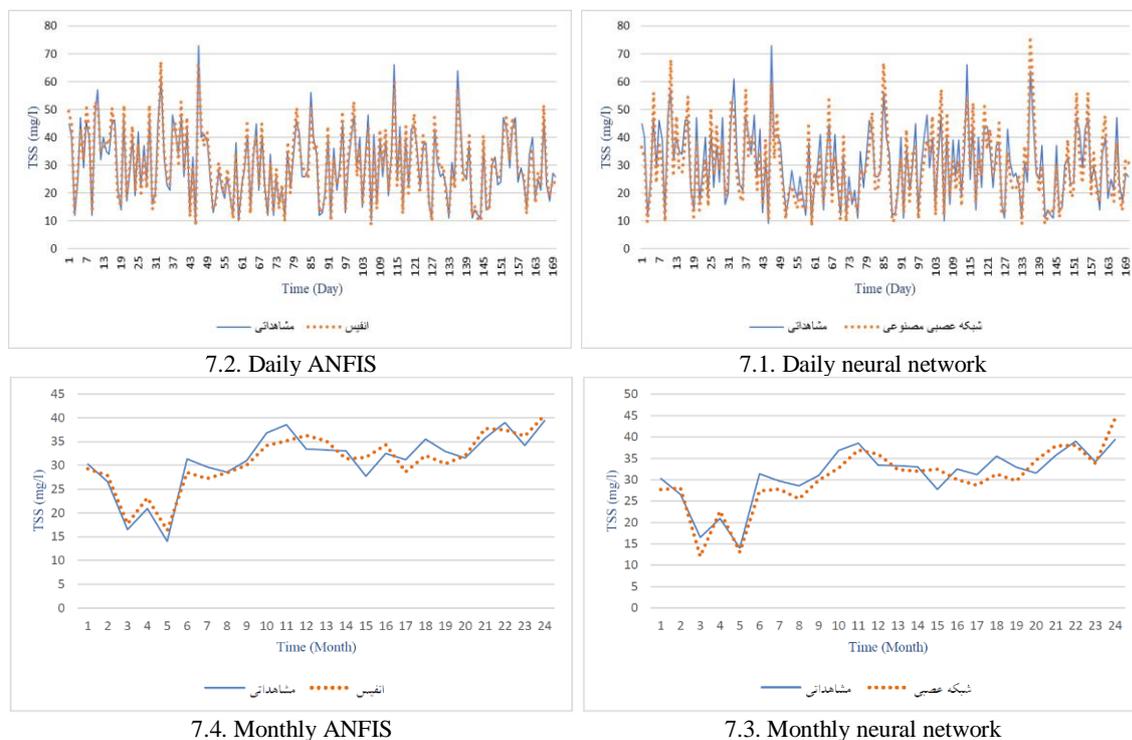


Fig. 7: Comparison of the output TSS values of the best models with the observational values in the validation stage

Table 4: The results of the best daily and monthly COD models

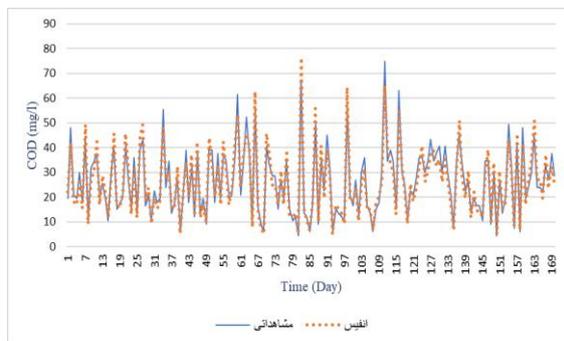
| Model type | Model name | Training rule of the neural network/ input membership function of the ANFIS | Activation function of the neural network/ output membership function of the ANFIS | Structure of the neural network | Coefficient of determination | | Root-mean-square error | |
|-----------------|------------------|--|---|---------------------------------|------------------------------|------------|------------------------|------------|
| | | | | | Training | Validation | Training | Validation |
| Neural, daily | CA ₁₂ | Levenberg-Marquart | tansig | 1, 17, and 6 | 0.94 | 0.82 | 0.0108 | 0.0128 |
| Neural, monthly | CA ₁₄ | Levenberg-Marquart | tansig | 1, 19, and 6 | 0.84 | 0.77 | 0.0302 | 0.0481 |
| ANFIS, daily | CA ₁₄ | pimf | linear | - | 0.97 | 0.87 | 0.0079 | 0.0102 |
| ANFIS, monthly | CA ₁₁ | gbellmf | linear | - | 0.93 | 0.87 | 0.0179 | 0.0231 |

5.3 Modeling the COD of the effluent of the sewage treatment plant

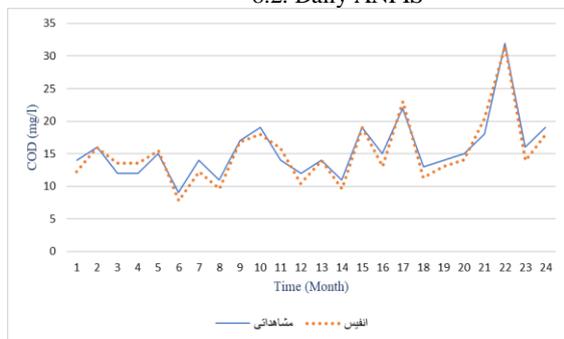
Given the reviewed studies and the collected data, the DO, COD, BOD₅, SVI, EC, and turbidity of the input sewage were used to model the COD of the output effluent in both neural network and the adaptive neuro-fuzzy inference system (ANFIS). Table 4 lists the results of the best daily and monthly models of the artificial neural network and adaptive neuro-fuzzy inference system (ANFIS).

The results of the model CA₁₂, which included the Levenberg-Marquart training function and tansig activation function, indicate that the artificial neural network could properly estimate the daily COD for the south Tehran sewage treatment plant. The structure of the CF₁₄ with the pimf input membership function and linear output

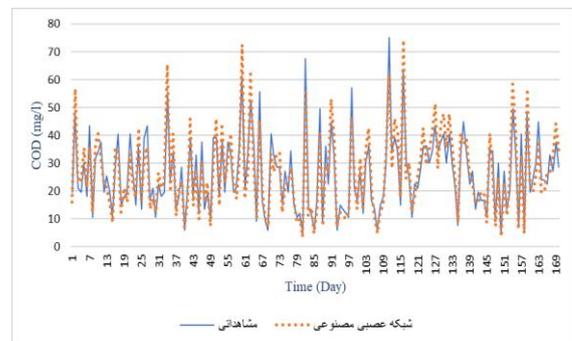
membership function shows the advantage of the adaptive neuro-fuzzy inference system over the neural network in daily models. The model CA₁₄ with the Levenberg-Marquart training function and tansig activation function (similar to the daily model) was able to properly estimate the monthly COD for the south Tehran sewage treatment plant while having a weaker performance compared to the daily neural model. The structure CF₁₁ with the gbellmf input membership function and linear output membership function was prior to the monthly neural network while showing weaker results compared to the daily ANFIS model. Fig. 8 provides the validation results of the best mentioned models.



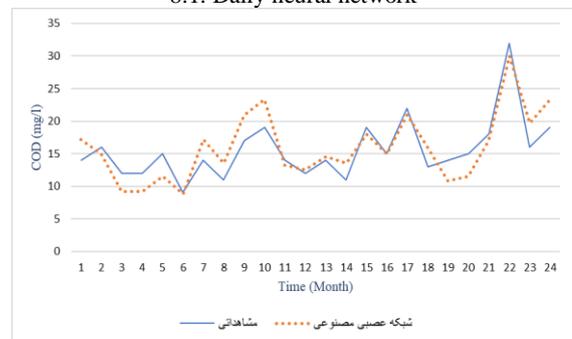
8.2. Daily ANFIS



8.4. Monthly ANFIS



8.1. Daily neural network



8.3. Monthly neural network

Fig. 8: Comparison of the output COD values of the best models with the observational values in the validation stage

5.4 Reuse of the wastewater of south Tehran treatment plant

According to the results obtained from the developed models, the daily ANFIS model (BF₁₀, TF₂₅, and CF₁₄) and monthly ANFIS model (BF₁₁, TF₂₇, CF₁₁) were used to estimate the BOD₅, TSS, and COD and control the quality of the wastewater obtained from the south Tehran sewage treatment plant. The BOD₅, COD, and TSS are among the most important indexes to evaluate the pollution level of sewage and compare it with different standards to reuse it or discharge it into water resources. Furthermore, measuring the BOD₅ and TSS in the laboratory requires considerable time and cost. Thus, by using the developed models and

comparing their results with the standard values shown in Table 1 for different wastewater uses, a proper classification can be provided to reuse the wastewater of the south Tehran sewage treatment plant. Table 5 provides samples of this control. The results show that the treated wastewater met the acceptable standard to be used in agriculture and irrigation uses. However, it should be evaluated to be discharged into surface water and groundwater. The tool provided in the model prepares the conditions for such evaluation of the south Tehran sewage treatment plant. It is worth mentioning that the obtained wastewater is transferred to the irrigation network of Varamin plain and used for irrigation of almost 50000 hectares of the lands.

Table 5: Control of the wastewater of the south Tehran sewage treatment plant to reuse it according to the standard of the Department of Environment

| Sample number | Daily | | | Monthly | | | Allowed to be discharged into the surface water | Allowed to be discharged into the groundwater | Allowed to be used for agriculture and irrigation |
|---------------|------------------|-------|-------|------------------|-------|-------|---|---|---|
| | BOD ₅ | COD | TSS | BOD ₅ | COD | TSS | | | |
| 1 | 41.23 | 64.24 | 58.21 | - | - | - | No | No | Yes |
| 2 | 35.68 | 55.42 | 49.53 | - | - | - | No | No | Yes |
| 3 | 29.46 | 47.05 | 38.63 | - | - | - | No | No | Yes |
| 4 | 22.56 | 37.11 | 32.62 | - | - | - | Yes | Yes | Yes |
| 5 | - | - | - | 33.76 | 54.63 | 41.63 | No | No | Yes |
| 6 | - | - | - | 26.68 | 42.56 | 31.42 | No | No | Yes |
| 7 | - | - | - | 22.32 | 33.66 | 28.63 | Yes | Yes | Yes |
| 8 | - | - | - | 17.57 | 27.88 | 22.14 | Yes | Yes | Yes |

5.5 Modeling the total solids (TS), volatile solids (VS), and specific oxygen uptake rate (SOUR) of the output sludge of the sewage treatment plant

Given the collected data, the TSS, COD, BOD₅, SVI, EC, and turbidity of the input sewage were used to model the VS, TS, and SOUR of the output effluent in both neural network and the adaptive neuro-fuzzy inference system (ANFIS). Table 6 lists the results of the best daily and monthly models

of the artificial neural network and adaptive neuro-fuzzy inference system (ANFIS).

The results of the selected models of the artificial neural network, which included the Levenberg-Marquart training function and tansig activation function, indicate that the artificial neural network could properly estimate the daily VS, TS, and SOUR of the sewage sludge for the south Tehran sewage treatment plant. However, the structures of the adaptive neuro-fuzzy inference system (ANFIS) was prior to the neural network in the daily models.

Table 6: The results of the best daily VS, TS, and SOUR models of the sewage sludge

| Model type | Model name | Training rule of the neural network/ input membership function of the ANFIS | Activation function of the neural network/ output membership function of the ANFIS | Structure of the neural network | Coefficient of determination | | Root-mean-square error | |
|--------------|-------------------|---|--|---------------------------------|------------------------------|------------|------------------------|------------|
| | | | | | Training | Validation | Training | Validation |
| Neural, TS | TSA ₁₂ | Levenberg-Marquart | tansig | 1, 17, and 6 | 0.85 | 0.80 | 0.0210 | 0.0335 |
| ANFIS, TS | TSF ₁₁ | gbellmf | linear | - | 0.87 | 0.80 | 0.0184 | 0.0200 |
| Neural, VS | VSA ₆ | Levenberg-Marquart | tansig | 1, 11, and 6 | 0.84 | 0.77 | 0.0333 | 0.0401 |
| ANFIS, VS | VSF ₉ | trimf | linear | - | 0.88 | 0.80 | 0.0351 | 0.0360 |
| Neural, SOUR | SOA ₅ | Levenberg-Marquart | tansig | 1, 10, and 6 | 15 | 0.83 | 0.79 | 0.0408 |

| | | | | | | | | |
|----------------|-------------------|---------|--------|---|------|------|--------|--------|
| ANFIS, SOUR | SOF ₁₁ | gbellmf | linear | - | 0.84 | 0.80 | 0.0372 | 0.0405 |
|----------------|-------------------|---------|--------|---|------|------|--------|--------|

5.6 Use of the sludge of the south Tehran sewage treatment plant as a fertilizer

According to the results obtained from the developed models, the daily ANFIS model (SOF₁₁, VSF₉, and TSF₁₁) can be used to control the sludge produced in the south Tehran sewage treatment plant. Table 7 provides the results of the tests on the developed models to control the sludge

obtained from the sewage treatment in the south Tehran plant. The results demonstrate that the obtained sludge had the required properties to be used as an agricultural fertilizer. It should be noted that the sludge currently produced in the plant can be used as a fertilizer in 6000 hectares of agricultural lands.

Table 7: Control of the sludge of the south Tehran sewage treatment plant to reuse it as a fertilizer

| Sample number | Daily model | | | Allowed to be used as a fertilizer |
|---------------|-------------|-------|------|------------------------------------|
| | TS | VS/TS | SOUR | |
| 1 | 0.27 | 0.32 | 0.95 | Yes |
| 2 | 0.29 | 0.35 | 1.11 | Yes |
| 3 | 0.32 | 0.36 | 1.23 | Yes |

6. Conclusion

The performance of sewage treatment plants is a function of various qualitative factors of the sewage, management conditions of the plant, and environmental issues. This study made an effort to employ the neural network model and fuzzy logic system to predict the intended qualitative parameters of the sewage treated in the south Tehran sewage treatment plant, as a case study, use the obtained wastewater, and finally classify the quality of the treated sewage and sludge. This study also aimed to make some comparisons between the two employed models and daily and monthly input data in prediction of qualitative parameters and classification of wastewater and sludge. The data required in this study were collected from the south Tehran sewage treatment plant. Then, using the MatLab software, a neural network model, and an adaptive neuro-fuzzy inference system (ANFIS), the qualitative parameters (COD, BOD₅, and TSS of the wastewater, along with TS, VS, and SOUR of the sludge) of the treated sewage were predicted and, finally, the best models were chosen by validating the model and using the defined criteria. The following provides a summary of the results:

- Acceptable results obtained from both models, i.e., the adaptive neuro fuzzy inference system and the artificial neural network, in predicting the qualitative properties of the sludge and wastewater of the south Tehran sewage treatment plant
- Advantage of the adaptive neuro fuzzy inference system over the neural network in estimating the quality of the treated wastewater and sludge
The better performance of the adaptive neuro-fuzzy inference system compared to the neural network due to ignoring the uncertainty which can indicate

an error in measuring various parameters caused by lack of appropriate experimental conditions, such

as suitable temperature, error of measurement tools, or human error.

- The advantage of the daily models in estimating the quality of the wastewater over the monthly models because of access to more data for training the model. As a result, in case of access to more monthly data, monthly models would be more reliable and be used for better resolution of future planning of south Tehran sewage treatment plant.
- Relatively lower error in estimating the BOD₅ of the wastewater compared to its COD and TSS with respect to the available data used for training the neural and fuzzy models. This does not establish more efficiency of the ANN and ANFIS in BOD₅ prediction. So, this gap would be reduced by access to more qualitative parameters of the wastewater which are correlated to COD and TSS.
- Relatively lower error in estimating the TS of the sludge compared to its VS and SOUR given the available data used for training the neural and fuzzy models. Similarly, to for wastewater, this gap would be reduced by access to more qualitative parameters which are correlated to VS and SOUR.
- Relatively lower error in estimating the qualitative properties of the wastewater compared to the sludge produced in the plant with respect to the available data used for training the neural and fuzzy models. This shows that available data is better suited for wastewater quality prediction which is focused more on the south Tehran sewage treatment plant.

- The priority of the Levenberg-Marquar training function and tansig activation function compared to the other training and activation functions existing for modeling the qualitative properties of the obtained sludge and wastewater using the artificial neural network
- The necessity of using a variable number of neurons in the hidden layer to achieve its optimum value for modeling the qualitative properties of the sludge and wastewater using the neural network model.
- The advantage of the input membership functions primf, trimf, trapmf, and gbellmf and the linear output membership function over other membership functions available for modeling the qualitative properties of the obtained sludge and wastewater using the adaptive neuro fuzzy inference system.
- The reuse of the output wastewater and sludge using selected models of the plant can be quickly evaluated according to the existing standards. Selected models give us both short- (daily) and long-term perspective in managing south Tehran sewage treatment plant.
- The test results of the models developed to control the wastewater obtained from the sewage treatment in the south Tehran plant indicate that the treated wastewater had allowable standard to be used in agriculture and irrigation, but it should be evaluated to be discharged into surface water and groundwater.
- The test results of the developed models to control the sludge obtained from the sewage treatment in the south Tehran plant show that the obtained sewage had the intended properties to be used as an agricultural fertilizer.
- The intended parameters of the wastewater and sludge can be estimated using the developed models. In particular, this can remarkably reduce the time, human force and costs required to measure the COD, BOD₅, and TSS of the wastewater.
- The selected models are appropriate to improve the efficiency of the sewage treatment plant, since based on these predictions, an operator can take the required measures before the problems occur, and thus, apply a proper control and operation.

Suggestions:

- The Researchers are recommended to apply methods like analysis of the major component to choose the most effective parameters in the BOD₅, COD, and TSS indexes of the output sewage. This can be achieved by using different combinations of the available input parameters.

- In order for better evaluation of the plant performance and more appropriate classification of the wastewater, it is recommended to model other parameters, such as pH, turbidity, and dissolved oxygen of the output wastewater produced from sewage treatment, in case of data availability.
- It is also suggested to use more recent modeling tools that haven't been used as much in engineering modeling of the environment, such as the wavelet neural network conjunction model or decision tree, and compare the results with those of the mentioned models.

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