ARTIFICIAL NEURAL NETWORK APPROACH FOR THE PREDICTION OF EFFLUENTS STREAMS FROM A WASTEWATER TREATMENT PLANT: A CASE STUDY IN KOCAELI (TURKEY)

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Abstract
A three-layer Artificial Neural Network (ANN) model was employed to develop and estimate the effluent stream parameters of two different wastewater treatment plants (WWTP) in Kocaeli, Turkey. The chemical oxygen demand (COD), suspended solid (SS), pH and temperature as the! output parameters were estimated by five input parameters such as flow rate, COD, pH, SS and temperature. The ANN model was developed with 400 data sets for prediction of effluent pH, temperature, COD and SS. The benchmark tests were employed to achieve an optimum network algorithm. The network model with optimum functions at hidden and output layers were applied for the forecasts of effluent streams of both WWTPs. The regression values of training, validation and test using this function were found as 0.94, 0.96 and 0.95, respectively. The optimum neuron numbers were determined according to the minimum mean square error values. ANN testing outputs revealed that the model exhibited well performance in forecasting the effluent pH, temperature, SS and COD values.

Keywords: Artificial neural network, Back propagation, Prediction, Waste Water Treatment Process

ATIKSU ARITMA TESİS ÇIKIŞ SUYUNUN YAPAY SİNİR AĞLARI İLE TAHMİNİ: KOCAELİ (TÜRKİYE) İLİ ÖRNEK ÇALIŞMASI

Özett
Bu çalışmada; Kocaeli (Türkiye) ilinde bulunan iki farklı atıksu arıtma tesis çıkış suyu parametreleri üç katmanlı Yapay Sınır Ağları (YSA) ile değerlendirilerek modelleme yapılmıştır. Çıktı parametreleri olarak belirlenen kimyasal oksijen ihtiyacını (KOİ), askıda katı madde (AKM), pH ve sıcaklık değerleri beş girdi parametresi (akış hızı, KOİ, AKM, pH ve sıcaklık) ile tahmin edilmiştir. YSA modeli 400 veri seti ile geliştirilerek çıkgış suyu pH, sıcaklık, KOİ ve AKM değerlerinin modellemesi yapılmıştır. YSA eğitimi için optimum algoritmayı belirlemek amacıyla birçok kıyaslama testleri gerçekleştirilmiştir. YSA modeli; gizli katmanda tanjant sigmoid transfer fonksiyonu (tansig) ve çıkış katmanında lineer transfer fonksiyonu (purelin) optimum olarak belirlenmiştir. Bu fonksiyonları kullanarak eğitim, validasyon ve test setleri için regresyon değerleri sırasıyla 0.94, 0.96 ve 0.95 olarak bulunmuştur. Gizli katmanda optimum nöron sayısı minumum ortalama kare hata değeri temel alınarak saptanmıştır. Elde edilen sonuçlara göre YSA modelinin çıkış suyu pH, sıcaklık, KOİ ve AKM değerlerinin tahmininde etkin ve doğru performans gösterdiği belirlenmiştir.

Anahtar Kelimeler: Yapay Sınır Ağları, Geri Yayılım, Tahmin, Atıksu Arıtma Prosesi

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1 Introduction
Among the chemometric methods, mathematical modelling offers cheap and fast option for the conventional analytic solutions which are useful to analyze the process structure and the correlations between the components [1]. Among the mathematical tools, artificial intelligence models such as artificial neural network (ANN), neuro-fuzzy (NF) or, fuzzy logic (FL) can efficiently overcome nonlinear and complex systems by
using numerical analysis [2], [3]. The ANN is a powerful tool involving the examination of a process by using network weights to obtain the desired response [4]. From an engineering point of view, ANN can be regarded as a heuristic model for predicting and classifying the data connecting from I/O data performance [5], and can be applied for modelling and controlling of nonlinear systems in processes [6], [7].

In the last decades, the application of artificial neural network has gained popularity in modelling wastewater treatment plants. In domestic and industrial usages, water quality is dependent on monitoring the key variable via obtaining the required impact of operation and ensuring the desired standards and protocols [8]-[12]. ANN predicts output data corresponding with input data after a learning period [13]. In addition, ANN has capability of learning non-linear functions without necessity for the structural process input [14]. Holubar et al. [15] developed feed forward ANN algorithm to estimate the methane production. Çınar [16] have found that the application of Kohonen self-organizing feature maps (KSOFM) neural network was efficient on the evaluation of WWTP performance. Chen et al. [17] applied ANN model to obtain well estimation for nitrogen amount in effluent streams. Nasr et al. [18] predicted Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD) and Total Suspended Solids (TSSs) data of a WWTP by using ANN with Feed Forward Back-Propagation. Dias et al. [19] applied ANN with neural fuzzy model for controlling and modelling the outputs of WWTPs. Harrou et al. [9] developed a machine learning model to detect potential mistakes in WWTPs. Raduly et al. [20] found the accuracy of ANN is sufficient with correlation coefficients $R^2 > 0.95$ and prediction errors lower than 10%, in order to apply in simulated WWTP. Nadiri et al. [21] proposed three FL models for a WWTP using influent water quality data (BOD, COD, pH, temperature, and TSSs). They have found that the trained ANN model provided a better estimation for the WWTP than the FL methods.

Although there are several ANN models for WWTPs have been proposed in literature, few studies were reported about the comparison of ANN modelling of WWTPs which have different influent properties. Therefore, the aim of this work was to investigate the ANN modeling to predict the effluent of two wastewater treatment plants in Kocaeli, Turkey. Kocaeli is one of the industrialized and urbanized cities in Turkey. The two WWTPs namely ‘Kullar’ and ‘42 Evler’ have different influent characteristics and the municipality has planned to combine these two WWTPs in one facility. Therefore, this research investigated and compared the prediction of effluent pH, temperature, COD and SS using feed-forward ANN trained with the back propagation algorithm.

## 2 Materials and Methods

### 2.1 Kullar and 42 Evler Wastewater Treatment Plants (WWTPs)

The Kullar WWTP treated municipal and industrial wastewater with an average capacity of about 20,000 m$^3$/day in summer and 27,726 m$^3$/day in winter months. The difference in flow rate is due to the by-pass stream of wastewater from balancing tank in rainy days winter months. The Kullar WWTP was a biological plant including activated sludge process to remove organic carbon and nitrogen. Between 2012–2014 years, the average influent stream capacity was 20,712 m$^3$/day including 43% industrial and 57% municipal wastewater.

The 42 Evler WWTP was established at 1988 and treated 60% municipal and 40% industrial wastewater by using activated sludge process. The plant comprised fine and coarse screens, inlet pump station, sand filters and ventilated air treatment, a pretreatment unit, activated sludge aeration tanks, sludge thickener and sludge dewatering system. The 42 Evler WWTP receives the wastewater of about 47 industries.

### 2.2 Wastewater Characteristics

The analysis of the wastewater characteristics in the WWTPs was carried out daily. In the composite samples, the COD, BOD, TSS, total phosphorus (TP), total nitrogen (TN), mixed liquor volatile suspended solids (MLVSS), pH, color and T (°C) are measured at the ISU Central Laboratories in Kocaeli. The COD, BOD, TSS, and MLVSS measurements were performed according to the standard methods. The TN and TP values were analyzed according to the methods of DIN EN ISO 11905-1 and TS EN ISO 11885, respectively. The pH and T (°C) are measured using electrometric method.

### 2.3 ANN Modelling

In this study, all data were separated into input matrix $[p]$ and target matrix $[t]$. Five process variables like influent pH, COD, flow rate, temperature, and TSS were selected as the ANN model inputs $[p]$, and effluent pH, temperature, COD and TSS were taken as the outputs $[t]$ (Fig. 1). The data were normalized in the range of [0, 1] according to the Eq.(1) as follows:

$$X_{\text{norm}} = 0.1 + \frac{(X_{\text{real}} - X_{\text{min}})}{(X_{\text{max}} - X_{\text{min}})} \times 0.88$$  \hspace{1cm} (1)
The Neural Network Tool module of MATLAB (The MathWorks, Inc., USA, R16) software was used for modelling and prediction. The Bayesian Regularization training algorithm was chosen as training algorithm. The experimental data set was classified into training (80%), validation (10%), and testing (10%) sets. In the current study, 400 data set were applied to develop ANN model for simulation of effluent pH, temperature, COD and SS. The best ANN model was evaluated based on the mean square error (MSE) and correlation coefficient ($R^2$) metrics.

3 Results and Discussion

3.1 Selection of optimum BP Training Algorithm

In the artificial neural network modelling, it is important to examine which training algorithm is optimum depending on the number of data points [22]. Therefore, 13 training algorithms were conducted to choose the best correlated BP algorithm (Table 1 and 2). A three-layer network with a tangent sigmoid transfer function (tansig) at hidden layer and a linear transfer function (purelin) at output layer, was applied in all algorithms. Ten neurons were used at the hidden layer for all BP algorithms. The results indicated that the traindx (Gradient descent w/momentum & adaptive lr backpropagation), with a minimum MSE (0.0033) was chosen as the best fitted back propagation algorithm for 42 Evler WWTP. The regression values of training, validation and test using this function were found as 0.94, 0.96 and 0.95, respectively (Fig. 2). The benchmark comparisons revealed that the MSE value (0.0035) of trainbr function was also calculated as smaller compared to batch gradient descent (trainld) and with momentum (trainldm) training algorithms.

### Table 1. Comparison of BP algorithms with ten neurons in the hidden layer (42 Evler WWTP)

| Function | R      | MSE     | Iteration Number |
|----------|--------|---------|------------------|
| trainbfg | 0.95443| 0.0041602| 39               |
| trainbr  | 0.96613| 0.0035403| 207              |
| traincgb | 0.95774| 0.0069559| 30               |
| traincfg  | 0.95774| 0.0073913| 59               |
| traincgp | 0.9569 | 0.0042638| 31               |
| traingd | 0.87316| 0.011423 | 1000             |
| trainldm | 0.90174| 0.010609 | 1000             |
| trainlda | 0.94341| 0.007636 | 137              |
| trainld | 0.95306| 0.0033168| 169              |
| trainlm | 0.95871| 0.0038147| 2                |
| trainoss | 0.95797| 0.0048177| 96               |
| trainrp | 0.95769| 0.0052998| 73               |
| trainscg | 0.95807| 0.0038887| 109              |

### Table 2. Comparison of BP algorithms with ten neurons in the hidden layer (Kullar WWTP)

| Function | R      | MSE     | Iteration Number |
|----------|--------|---------|------------------|
| trainbfg | 0.96384| 0.00092502| 58               |
| trainbr  | 0.96734| 0.0023474| 564              |
| traincgb | 0.96054| 0.0012083| 38               |
| traincfg  | 0.96361| 0.0011186| 89               |
| traincgp | 0.9572 | 0.0042441| 19               |
| traingd | 0.82576| 0.018563 | 1000             |
| trainldm | 0.95993| 0.0013348| 5000             |
| trainlda | 0.94453| 0.0021232| 131              |
| trainld | 0.81455| 0.013858 | 66               |
| trainlm | 0.96645| 0.0033744| 8                |
| trainoss | 0.96027| 0.0016085| 40               |
| trainrp | 0.95949| 0.0011929| 81               |
| trainscg | 0.94576| 0.0052459| 12               |
validation and testing was investigated for both WWTPs and the results are shown in Table 3. According to the high regression coefficients, three-layer feed-forward ANN model with tansig at hidden layer and purelin at output layer were found optimum for the forecasts of effluent streams of both WWTPs.

| Run | Function | Neuron number | Regression performance |
|-----|----------|---------------|------------------------|
|     |          |               | Training | Validation | Test |
| 42 Evler WWTP | Tansig, Purelin | 10 | 0.948 | 0.969 | 0.953 |
| 2   | Tansig, Logsig | 10 | 0.856 | 0.858 | 0.833 |
| 3   | Tansig, Tansig | 10 | 0.950 | 0.962 | 0.942 |
| 4   | Logsig, Purelin | 10 | 0.866 | 0.831 | 0.864 |
| 5   | Logsig, Tansig | 10 | 0.940 | 0.926 | 0.930 |
| 6   | Logsig, Logsig | 10 | 0.847 | 0.836 | 0.863 |
| Kullar WWTP | Tansig, Purelin | 10 | 0.967 | 0.989 | 0.924 |
| 2   | Tansig, Logsig | 10 | 0.952 | 0.982 | 0.954 |
| 3   | Tansig, Tansig | 10 | 0.975 | 0.908 | 0.970 |
| 4   | Logsig, Purelin | 10 | 0.958 | 0.953 | 0.980 |
| 5   | Logsig, Tansig | 10 | 0.959 | 0.986 | 0.929 |
| 6   | Logsig, Logsig | 10 | 0.355 | 0.333 | 0.364 |

### 3.2 Optimization of ANN Structure

The key section of training the ANN model is to determine the most suitable number hidden layers and number of neurons per layer [12]. The larger networks can result in higher precision in the dataset, but leading an overfitting the model [23]-[24]. Thus, it is important to apply the least number of hidden layers and neurons which ensures high accuracy for both training and estimation. Anupam et al. [25] indicated that application of more hidden layer would lead the system more complex and increase the time. For this reason, the number of hidden layer was kept constant and the tests were conducted between MSE and neuron numbers in the hidden layer. At first, two neurons were applied in hidden layer and then the neuron numbers were increased and varying MSE values were calculated for the training set.

After selecting the best algorithm, the optimum activation function for a maximum regression value for training,
Fig. 4 shows the dependence between the neuron number and MSE. For 42 Evler WWTP, the optimal neuron number was found to be 12 neurons (MSE 0.003) while that of for Kullar WWTP was found as 10 neurons (MSE 0.0009) for the estimation of output parameters. When the number of neurons decreased from 12 to 8, the MSE value increased significantly from 0.003 to 0.014, for the 42 Evler WWTP. Similar phenomena was observed for Kullar WWTP. This increment could be attributed to the MSE performance index, and the properties of the input vectors [22]. It can be concluded that, ANNs are highly dependent on the number of neurons in their hidden layers. Yetilmézsöy et al. [22] indicated that the low neuron numbers could result in under-fitting, while higher neurons in hidden layer could lead to overfitting in which the fitting curves is composed of sharp oscillations. After selecting the optimum neuron numbers for WWTPs, the MSE graphics for the prediction of effluent streams of WWTPs were drawn as shown in Fig. 5.

3.3 Prediction of Effluent Parameters of WWTPs

The ANN modelling was performed between the observed output and the model response. The comparison between the corresponding data and the ANN outputs indicated that the predicted data were agreed with the experimental one (Fig. 6). The results indicated that the ANN method with smaller deviation showed a good simulation performance for estimating the water parameters namely pH, Temperature, COD and SS. In Kullar WWTP, the data between April, 2013 and March, 2014 were missing due to the interruption in the plant. So, the data between these periods could not be evaluated during the ANN modelling.

Fig. 6(a) shows the comparison of effluent pH values of WWTPs. The pH of influent streams of 42 Evler WWTP were in the range of 7.0–8.0; while that of for Kullar WWTP were 6.3–7.5. The determination coefficient values ($R^2 = 0.878$ and 0.852) for testing sets indicated that 12.2% and 14.8% of the total variations were not defined by the ANN method in the estimation of output pH values for 42 Evler and Kullar WWTPs, respectively.

Since the influent temperature has a significant effect on the municipal WWTPs combined with seasonal temperature changes. As shown in Fig 6(b), ANN model outputs presented a very small deviation of about 0.02 and 0.01 from the experimental data ($R^2 = 0.9725$ and 0.9864) for 42 Evler and Kullar WWTPs, respectively. The high correlation may be attributed to the fact that the temperature is not significantly affected by any treatment process; while it depends on the seasonal change. The estimation of suspended solids (SS) is essential in controlling the quality of effluent stream since SS are classified as one of the major pollutants decreases the water quality. The input, observed and ANN testing output SS values were shown in Fig. 6(c). For both WWTPs, the observed output SS values were highly changed according to the unlimited concentrations –up to 2000 mg/L- at some
Figure 6. Comparison of visual agreements between the experimental and ANN simulations in estimation of output wastewater characteristics of (a) pH, (b) Temperature (°C), (c) SS and (d) COD
months. The ANN model did not successfully predicted the effluent SS values especially above the boundary concentrations. Although ANN can deal with noisy and erroneous data, the process conditions in biological WWTPs change steadily and relative error in these might hinder the ANN model [26]. Therefore, after neglecting the exceeded concentrations, the correlation coefficients between ANN predicted outputs and measured values were calculated to be 0.7456 and 0.7248, for 42 Evler and Kullar WWTPs, respectively.

Fig. 6(d) shows the COD values of observed and predicted output and also influent streams of WWTPs. The COD of influent streams of 42 Evler WWTP were in the range of 300–3000 mg/L; while that of for Kullar WWTP were 200–750 mg/L. The significant difference of COD values in the WWTPs could be due to the fact that the Kullar WWTP receives mainly domestic influent while 42 Evler WWTP receives a complex mixture of industrial and domestic wastewater. Therefore, the prediction of effluent of Kullar WWTP was found more accurate (R² = 0.924) when compared with 42 Evler WWTP (R² = 0.873).

In Turkey, the continuous prediction of COD is vitally important in each WWTP as it is essential to decrease the effluent quality below the standard for 90% of the time [Moral-2008]. However, the analysis of COD is difficult and time consuming. Therefore, in the current work, the applied ANN model with high accuracy is important for efficiently prediction of COD values in the effluent on a real time basis.

4 Conclusion
The estimation of effluent stream properties in the WWTPs is a critical issue due to the environmental effects of the water quality. However, the measurement of the parameters can be difficult and take days to obtain the analysis results which increased the cost. Herein, the applicability of artificial neural network technique in the estimation of effluent parameters has been demonstrated. The three-layer ANN model presented acceptable predictions on four effluent parameters with satisfactory determination coefficients. The optimum neuron values in the hidden layer were obtained as 12 and 10 with the related MSE numbers of 0.003 and 0.0009, for the prediction of output parameters of 42 Evler and Kullar WWTPs, respectively. Statistical performance revealed that the suggested ANN model had a great predictive accuracy on simulation of pH, temperature, SS and COD values of effluent streams.

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