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Determination of the Effects of Some Water Quality Parameters on Turbidity Parameters in Filyos River with Artificial Neural Network

Filyos Nehri'nde Bazı Su Kalitesi Parametrelerinin Bulanıklık Parametresi Üzerine Etkilerinin Yapay Sinir Ağı ile Belirlenmesi

Berna Aksoy[1]*, İsmail Hakkı Özölçer[1], Emrah Doğan[2]

[1]Zonguldak Bulent Ecevit University, Faculty of Engineering, Civil Engineering Department, Zonguldak, Türkiye
[2]Sakarya University, Faculty of Engineering, Civil Engineering Department, Sakarya, Türkiye

Abstract

During the water cycle, substances that are contaminated in water cause physical, chemical or biological alterations of the water's natural features, therefore environmental balance deteriorate over time. Observations and measurements on a river give the necessary information about how to benefit from the river. For this reason, it is important to investigate the water quality in rivers and water reservoirs which are close to settlement areas. In this study, surface water quality measurements were carried out at five observation stations along the main line of the Filyos River, which forms the largest sub-basin in the Western Black Sea Basin, at intervals of thirty days in 2015 year. The turbidity parameter was estimated by artificial neural networks (ANNs) based on water quality parameters such as chromium (Cr^{+3}), chemical oxygen demand (COD), iron (Fe^{+3}), aluminium (Al^{+3}), suspended solids, manganese (Mn^{+2}), zinc (Zn^{+2}), lead (Pb^{+2}) and calcium (Ca^{+2}). The study was conducted with creating two scenarios. In the first scenario, the determined parameters were analyzed by ANN for each station one by one. The obtained data showed that Cr (coefficient of determination [R^2] =0.9999) parameter gave the best performance in the estimation of turbidity parameter in the study area. In the second scenario, eight models were created by adding the other best performing parameters one by one to the best performing Cr parameter. The third model formed by Cr, COD, Fe and Al parameters gave the closest result with R^2=0.9992.

Keywords: Artificial neural network, Filyos river, turbidity, water quality

Öz

Su döngüsü sırasında suya bulaşan maddeler, suyun fiziksel, kimyasal veya biyolojik özelliklerini değiştirerek su kirliliğine yol açar ve zamanla çevresel dengenin bozulmasına neden olur. Bir nehir üzerinde yapılan gözlemler ve ölçümler, nehirden nasıl yararlanılacağı konusunda gerekli bilgileri verir. Bu nedenle yerleşim yerlerine yakın olan akarsularda ve su depolarında su kalitesinin araştırılması önemlidir. Bu çalışmada, Batı Karadeniz Havzası'nın en büyük alt havzasını oluşturan Filyos Nehri'nin ana hattı boyunca uzanan beş gözlem istasyonunda bir yıllık periyotta otuz gün aralıklarla yüzeysel su kalitesi ölçümleri yapılmıştır. Su kalitesi parametrelerinden, krom (Cr^{+3}), kimyasal oksijen ihtiyacı (COD), demir (Fe^{+3}), alüminyum (Al^{+3}), askıda katı madde, mangan (Mn^{+2}), çinko (Zn^{+2}), kurşun (Pb^{+2}) ve kalsiyum (Ca^{+2}) parametrelerine dayalı olarak bulanıklık parametresinin yapay sinir ağları (YSA) ile tahmini yapılmıştır. Çalışma iki senaryo üzerinden yürütülmüştür. Birinci senaryoda belirlenen parametreler, her istasyon için tek tek YSA ile analiz edilmiştir. Elde edilen veriler, çalışma alanında, bulanıklık parametresi tahmininde en iyi performansı Cr (R^2=0.9999) parametresinin verdiğini göstermiştir. İkinci senaryo da ise en iyi performansı veren Cr parametresine diğer en iyi performansı veren parametreler tek tek eklenerek sekiz model oluşturulmuştur. Cr, KOİ, Fe ve Al parametrelerinin oluşturduğu üçüncü model R^2=0.9992 gerçeğe en yakın sonucu veren model olmuştur.

Anahtar Kelimeler: Bulanıklık, Filyos nehri, su kalitesi, yapay sinir ağı

*Corresponding author: berna.oaksoy@beun.edu.tr

Berna Aksoy orcid.org/0000-0001-6925-1594
İsmail Hakkı Özölçer orcid.org/000-0002-8404-0522
Emrah Doğan orcid.org/0000-0001-5077-6518

1. Introduction

The Earth is predominantly covered by water, with approximately 71% of its surface covered by this vital resource. Of this, 97.5% is found in oceans and seas as saltwater, while the remaining 2.5% is freshwater found in rivers and lakes. Approximately 90% of the world's freshwater resources are trapped in the polar zones and underground.Accessible freshwater, which is essential for all living creatures, is limited to only 0.3% of the world's water resources (Aksoy, 2018).Water pollution can be caused by a variety of sources, including domestic and industrial waste, chemical fertilizers (especially nitrogen fertilizers) used in agriculture, air pollution (such as acid rain), and undesirable hazardous substances transported by erosion, such as soil and foreign matter.

Numerous international and national scientific studies have been conducted on rivers, which are considered to be particularly scarce water resources in the world's usable fresh water. These studies aim to determine current and potential levels of pollution, evaluate water quality based on physical and chemical parameters in the study areas, and provide information on the current quality level to ensure human sustainability.

Metals that are denser than 5.00 g/mL are called heavy metals. More than 60 metals are included in this group e.g., zinc (Zn), lead (Pb), cadmium (Cd), iron (Fe), copper (Cu), nickel (Ni), and carbon monoxide (CO) (Bakar & Baba 2009). Sometimes, wastewaters may contain high concentrations of heavy metals and these metals rate important problems in aquatic environments and for creatures living in these environments via the usage of natural resources and human activities (Kaçar et al. 2022).

Water quality modeling studies for rivers and water reservoirs were started in the 1970s. Besides, water quality and multi-dimensional hydrodynamic models on rivers and water resources have been done and confirmed by various computing methods (Aksoy 2018).

In those studies, surface water quality parameters are measured in situ and in laboratories [dissolved oxygen (DO), temperature (°C), pH, electrical conductivity (EI), suspended solids (SS), chemical oxygen demand (COD), turbidity, total organic carbon (TOC), ammonium (NH_4^+), calcium (Ca^{+2}), magnesium (Mg^{+2}), hardness, sodium (Na), copper (Cu), chloride ion (Cl), potassium (K), phosphate (PO_4^{-3}), nitrite (NO_2-), nitrate (NO_3-), aluminum (Al^{+3}), manganese (Mn^{+2}), iron (Fe^{+3}), chromium (Cr^{+3}), lead (Pb^{+2}) and zinc (Zn^{+2})] and the quality of water is classified. In addition, these measured parameters are statistically analyzed; modern methods, such as artificial neural network (ANN) and Fuzzy Logic are used for accurate prediction of various parameters (Gürsoy et al. 2018, Sonmez et al. 2018, Leventeli and Yalçın 2019, Atıcı 2020, Demirel 2021, Çıtakoğlu and Özeren 2021, Oskay et al. 2022, Kaya 2022, Aslan 2023).

In this study, surface water quality parameters (COD, Ca^{+2}, Al^{+3}, Mn^{+2}, Fe^{+3}, Cr^{+3}, Pb^{+2} and Zn^{+2}, turbidity and SS) are measured seasonally at five observation stations located along the main line of the Filyos River (228 km) at intervals of thirty days in 2015 (i.e. one-year period) and analyzed in the laboratory. In water quality studies, turbidity parameter based on Al^{+3}, Fe^{+3}, Mn^{+2}, Zn^{+2}, Pb^{+2}, Cr^{+3}, Ca^{+2} and SS parameters is predicted by ANN method using matrix laboratory (MATLAB). Then, the highly efficient model is determined by adding more efficient parameters one by one to this parameter. The results of the proposed model show that the results obtained from ANN are not different from the measured values in the laboratory and in situ. So that, ANN can be successfully applied and produces reliable estimations.

2. Material and Methods

2.1. Study Area

The length of the Filyos River is 228 km, the annual flow regime of river is quite regular, and its water level increases in winter and spring seasons whereas it decreases towards to the end of summer. The Filyos basin with drainage area of 13.300 km^2, covers surface area of about 46% of the Western Black Sea Basin. Filyos River carries in average 2.9 km^3/year water and 4.2 million ton/year sediment. With this feature, Filyos River is ranked as 5th river with a fresh water capacity of 7% in Türkiye (Küçükali 2019). Karabük Iron-Steel Factory and Seka Çaycuma Paper Factory, located in this region, cause pollution of the river considerably. Besides, the main factor, polluted the river, is that the regional administrations dump domestic sewage and garbage into the river for years (Demirci 2008).

General Directorate of State Hydraulic Works (DSİ) determined the locations of five stations on the Filyos River by considering the factors such as proximity to agricultural lands, industrial facilities and population density (Figure1, Table 1).

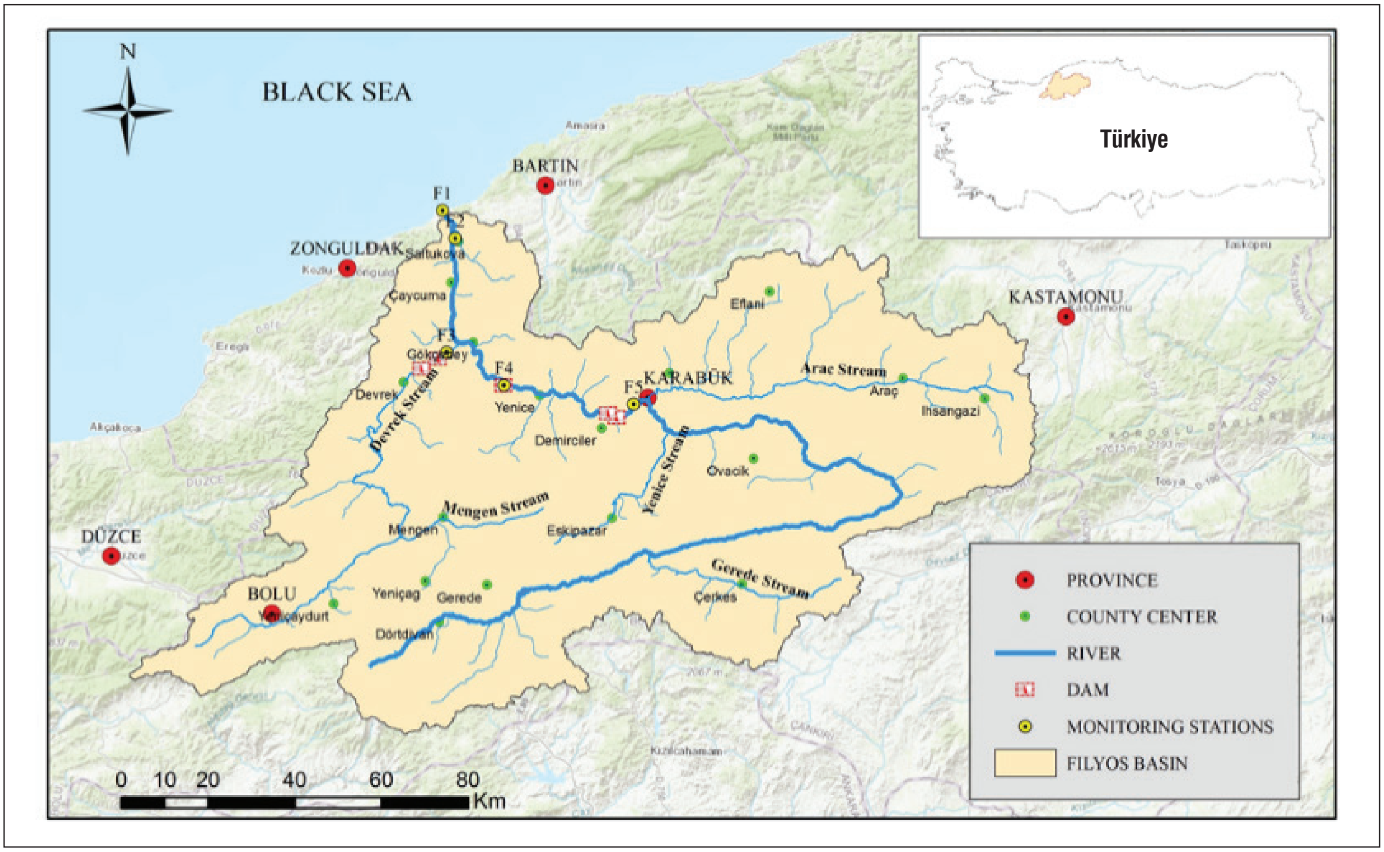

Figure 1. Locations of five water quality measurement stations on the Filyos River (Aksoy 2018).

Table 1. Coordinates of five water quality measurement stations along the Filyos River.

Stations	Coordinates	Height (m)
F1 (Filyos)	41°34’45.91”N - 32° 2’55.88”E	11
F2 (Saltukova Bridge)	41°31’20.68”N - 32° 5’11.09”E	56
F3 (Çaydeğirmeni)	41°17’2.83”N - 32° 4’9.88”E	59
F4 (Tefen HEC)	41°13’14.00”N - 32°13’31.00”E	98
F5 (Karabük)	41°11’9.21”N - 32°35’25.83”E	301

2.2. Model and Methods

In 2015, water samples were collected monthly from five different water quality monitoring sites and physicochemical parameters were analyzed both in the field using portable equipment and in the laboratory using standard methods. (Eaton et al. 2005, Clesceri et al. 1998). The results obtained at the laboratory are given in Table 2.

The turbidity monthly values were predicted by using ANN model. ANN toolbox in MATLAB was utilized for analyzing the model. In creating the model, the data set were divided into two parts: Training set and validation set. In this context, 420 of the 480 data collected in the study were used to train the artificial neural network, while the remaining data (60 data) were used to test the accuracy of the model. The surface water quality parameters were evaluated seasonally for each station one by one. The proposed model was trained separately for each station.

ANN is the distributed and parallel data processing structures that are inspired by human brain, connected by means of the weighted connections and consisted of processors having their own memory. In other words, it is a general expression of computer programs that mimic biological neural networks

(Elmas 2003). The most important property of initial models of ANN is that they can solve linear events. They have been encountered difficulties on learning the non-linear relations. Therefore, multilayer perceptron (MLP) was developed. MLP is a forward connection networks and composed of three layers: Input layer, hidden layer, and output layer (Figure 2) (Öztemel 2016).

Table 2. Results of water quality measurements.

Station	Season	Al^{+3}	Mn^{+2}	Fe^{+3}	Cr^{+3}	Pb^{+4}	Zn^{+2}	Ca^{+2}	SS	COD	Turbidity
F1	Autumn	10.23	0.28	20.46	0.26	0.02	0.31	51.98	46.00	111.50	97.10
	Winter	16.37	0.41	17.29	0.31	0.02	0.190	53.74	50.50	92.50	73.75
	Spring	3.24	0.48	53.94	0.21	0.04	0.49	55.19	84.00	83.23	54.98
	Summer	7.07	0.09	11.32	0.09	0.02	0.34	53.49	135.50	65.42	49.92
F2	Autumn	13.20	0.49	30.49	0.23	0.51	0.36	55.47	44.00	116.50	17.80
	Winter	19.67	0.14	40.08	0.24	0.07	0.18	58.20	40.50	82.50	20.85
	Spring	12.15	0.16	48.86	0.15	0.10	0.64	59.83	60.50	80.03	14.40
	Summer	4.42	0.06	46.54	0.09	0.01	0.54	90.65	90.00	79.60	47.65
F3	Autumn	2.62	0.43	23.10	0.10	0.03	0.45	56.74	24.00	55.00	10.21
	Winter	4.56	0.49	26.35	0.15	0.03	0.62	49.73	52.00	52.00	10.77
	Spring	7.63	0.35	34.87	0.16	0.0	0.58	58.98	79.00	57.36	12.20
	Summer	2.96	0.05	48.02	0.08	0.01	0.56	62.37	95.50	100.97	13.04
F4	Autumn	2.80	0.25	41.09	0.09	0.03	0.34	56.89	27.00	74.50	15.58
	Winter	4.54	0.29	36.36	0.10	0.02	0.49	53.59	54.50	86.50	23.42
	Spring	6.11	0.23	46.75	0.11	0.02	0.49	62.56	103.00	70.00	30.01
	Summer	4.41	0.08	39.71	0.07	0.01	0.58	59.54	108.50	80.50	13.61
F5	Autumn	3.55	0.07	76.08	0.06	0.04	0.23	57.03	57.50	108.00	21.60
	Winter	4.50	0.11	57.37	0.05	0.01	0.36	55.45	77.50	137.00	36.70
	Spring	3.89	0.11	58.64	0.05	0.01	0.40	62.13	156.00	89.56	51.48
	Summer	6.19	0.10	24.39	0.07	0.01	0.59	54.71	148.50	74.17	16.62

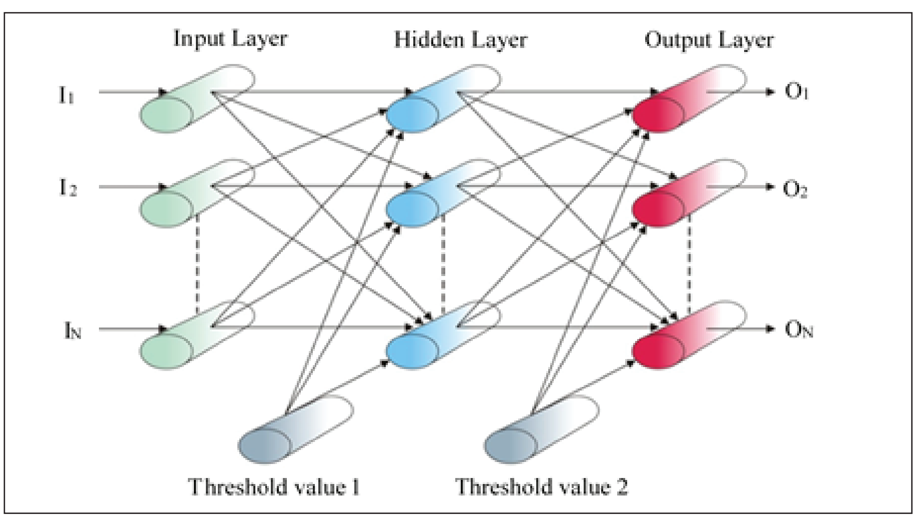

Figure 2. Multi-layer perceptron.

Multilayer perceptron neural networks operate in comparison with supervised learning model. It means that both inputs and expected outputs are generated in response to these inputs introduce to the networks during the training of the networks. The learning rule of multilayer perceptron is the generalized condition of the Delta Rule based on least squares method. Generalized Delta Rule involves two phases. First phase is the calculating phase of the network output named forward calculation. The second phase is the phase of change the weights known as backward calculation (Öztemel 2016). The operations performed in these two phases can be briefly described as follows.

In the preparation phase, ANN topology analysis was performed to determine the number of ANN hidden layer neurons. For different hidden layer neuron numbers, ANN performances, coefficient of determination (R^2) and mean squared error (MSE) statistical performance analysis criteria were used. ANN topologies were trained and tested by taking the number of hidden layer neurons as 3, 4, 6, 8 and 10 respectively. Then, selected parameters for analyses were put to the system as input individually, and it was determined which parameter estimates accurately turbidity (Table 3).

Table 3. Models created for different input layers.

Model No	Input Variables	Output
1	Cr	Turbidity
2	COD	Turbidity
3	Fe	Turbidity
4	Al	Turbidity
5	SS	Turbidity
6	Mn	Turbidity
7	Zn	Turbidity
8	Pb	Turbidity
9	Ca	Turbidity

Afterwards, at each time, it has been added the other most accurate parameter to the most accurate one for estimation of turbidity. The most effective model for turbidity parameter was determined as regarding to the proposed model based on basin. (Table 4).

Table 4. Models created for different input layers.

Model No	Input Variables	Output
1	Cr, COD	Turbidity
2	Cr, COD, Fe	Turbidity
3	Cr, COD, Fe, Al	Turbidity
4	Cr, COD, Fe, Al, SS	Turbidity
5	Cr, COD, Fe, Al, SS, Mn	Turbidity
6	Cr, COD, Fe, Al, SS, Mn, Zn	Turbidity
7	Cr, COD, Fe, Al, SS, Mn, Zn, Pb	Turbidity
8	Cr, COD, Fe, Al, SS, Mn, Zn, Pb,Ca	Turbidity

3. Results and Discussion

In the study, firstly, the water samples were collected at thirty-day intervals between September 2015 and August 2016 at five water quality measurement stations on the Filyos River. Secondly, some of them were analyzed in situ with portable devices and the others at the laboratory and then ANN was applied to the results obtained from the analyses. The study showed that the Cr parameter was the best for predicting turbidity in water with accuracy of 99%. Figure 3 shows the topology plot of the Cr parameter with the best performance in test. Cr parameter is respectively followed by COD, Fe, Al, ECM, Mn, Zn, Pb and Ca parameters (Table 5).

Table 5. Model results for different input layers.

No	Parameter	The Number of Hidden Layer	R^2	MSE
1	Cr	8	0.9999	$6{,}6612.10^{-6}$
2	COD	10	0.9987	0.000584
3	Fe	8	0.9980	0.00093
4	Al	6	0.9963	0.0001
5	SS	10	0.9944	0.00026
6	Mn	3	0.9938	0.0002
7	Zn	6	0.9900	0.0006
8	Pb	6	0.9878	0,00059
9	Ca	8	0.9764	0.0011

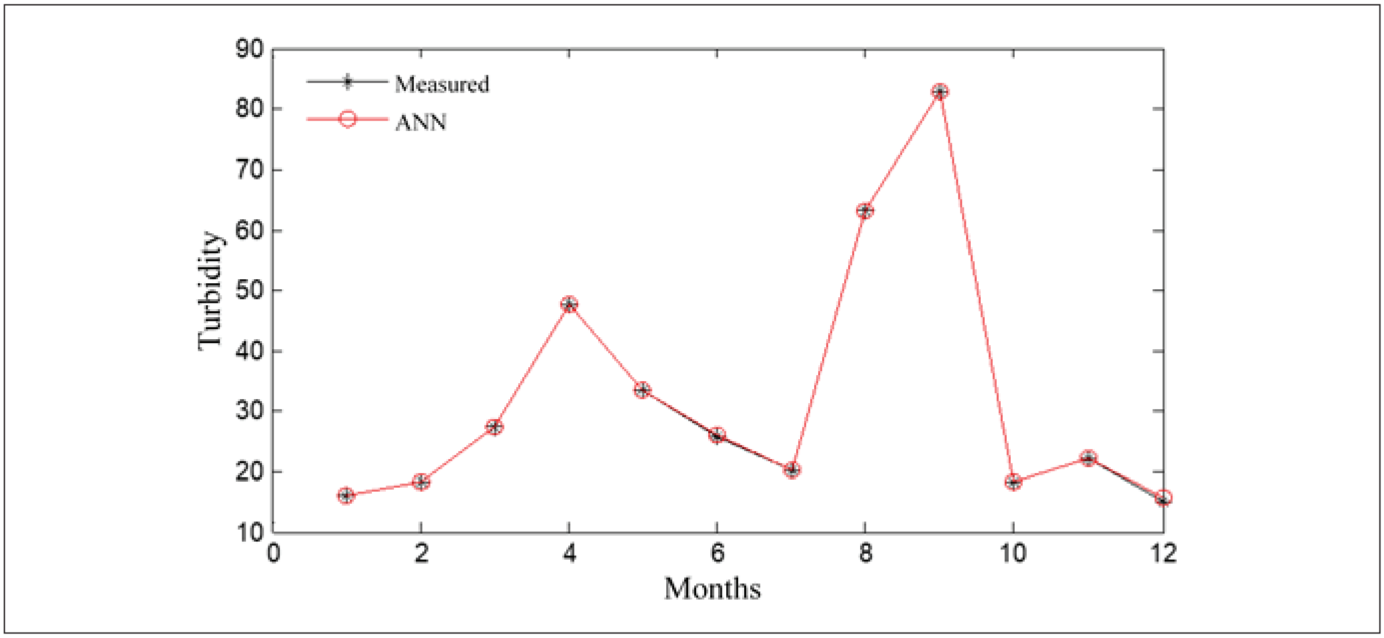

Figure 3. ANN performance for Cr in Filyos River.

Table 6. Results for different input layers.

No	Supplemented Parameters	The Number of Hidden Layer	R^2	MSE
1	Cr, COD	8	0.9624	0.00220
2	Cr, COD, Fe	4	0.9795	0.00120
3	Cr, COD, Fe, Al	10	0.9992	0.000046
4	Cr, COD, Fe, Al, SS	6	0.9884	0.000067
5	Cr, COD, Fe, Al, SS, Mn	10	0.9941	0.00034
6	Cr, COD, Fe, Al, SS, Mn, Zn	10	0.9983	0.000099
7	Cr, COD, Fe, Al, SS, Mn, Zn, Pb	6	0.9978	0.00013
8	Cr, COD, Fe, Al, SS, Mn, Zn, Pb, Ca	10	0.9972	0.00016

Besides, the results of the models formed by adding the subsequent best parameter to Cr parameter at each step are given in Table 6. The topology graph that illustrates the best performance of parameters in test is given in Figure 4.

4. Conclusion and Suggestions

Water management in Turkey, where water resources are limited, should be continued by developing more appropriate policies. Protecting and improving water quality are very important in this process. Artificial neural networks (ANNs), which have significant achievements in the modelling studies, for forecasting water quality parameters are used. In this study, ANN models were created to predict the turbidity parameter, which is one of the water quality parameters of the Filyos River between 2015-2016 years. The models, developed for this study, were considered together and water quality parameters that have been selected for forecasting turbidity in the Filyos River are used one by one as input to the system.

Then, the best estimated parameter for turbidity has been determined. The model resulted that Cr parameter was the most importance parameter for predicting turbidity parameter. The parameters of COD, Fe, Al, SS, Mn, Zn, Pb and Ca followed Cr, respectively. New models were formed by adding the subsequent best parameter to Cr parameter

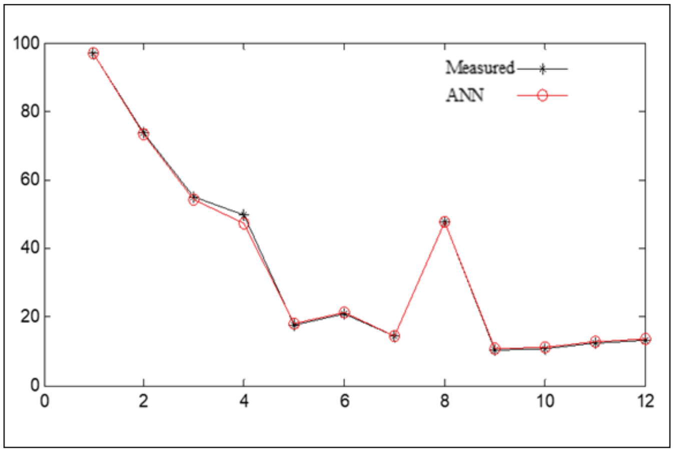

Figure 4. AAN performance for Cr, COD, Fe and Al parameters.

at each step. The results of the third model showed that Cr, COD, Fe and Al were more accurate estimation parameters for the turbidity. It was found that the results of ANN models were very close to the measured values at laboratory and in situ with portable devices. The study demonstrated that ANN is an available tool for predicting turbidity in water resources successfully and accurately.

Author contribution: İsmail Hakkı Özölçer and Emrah Doğan guided the study and Berna Aksoy contributed to data collection, analysis and modeling.

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