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Evaluation of Deep Sea Discharge Systems Efficiency in the Eastern Black Sea Using Artificial Neural Network: a Case Study for Trabzon, Turkey

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HIGHLIGHTS

- To evaluate deep sea discharge systems efficiency using the neural network.
- Neural network technique uses extensively in environmental engineering.

Abstract: The aim of this study is to evaluate the parameters such as pH, dissolved oxygen, temperature, conductivity, salinity, biological oxygen demand (BOD), total suspended solid, ammonia, chlorophyll-a and heavy metals affecting total coliform values in seawater using Artificial Neural Network (ANN) modelling at the Eastern Black Sea coast of Turkey. The results obtained from ANN model were compared with actual total coliform values. The samples were taken from the different points selected along the deep sea discharge systems starting from the diffuser end of three domestic deep sea discharge systems at Turkey's Eastern Black Sea coast. ANN model was developed for estimating the relationship between total coliform and other parameters. The parameters measured in seawater samples were analyzed by using the ANN model for prediction of coliform values. The results showed that neural network model is capable of estimating the sea pollution with a reasonable accuracy.

Keywords: Artificial Neural Network; Black Sea; Deep Sea Discharge; Total Coliform; Trabzon.

INTRODUCTION

Sea outfalls are designed to effectively dispose of partially or completely treated wastewater in coastal communities. The major purpose is to use the natural assimilating capacity of gigantic water bodies to minimize the harmful impact of the discharged wastewater [1]. The discharge of domestic or industrial wastewater into coastal waters represents a major cause of marine and estuarine pollution in many countries around the world. Especially, the common dumping of sewage without primary treatment is of major concern, as these effluents not only contain high concentrations of suspended solids and nutrients but often also carry substantial amounts of human organic waste products (e.g. feces) [2]. Submarine outfalls, encountered in the last step of the effluent treatment, are one of the most important sanitation infrastructures used nowadays, is almost inevitable that the chosen places for the final effluent disposal will be the sea and the estuaries [3]. The Black Sea, which is an inland sea, located between$41^oN - 46^oN$ and $28^oE - 42^oE$, connected to the Sea of Marmara via the Bosporus Strait and the Azov Sea by the Kerch Strait, has a surface area of 413,490 km^2, a total volume of 537,000 km^3, also maximum and average depth nearly 2200 m and 1300 m, respectively [4]. The Black Sea, which is a large depositional basin for rivers discharging waters from Southeastern Europe, Caucasian Mountains and Northern Anatolia, has long been an important basin for studying extreme anoxic oceanographic conditions, because it is considered as the world's largest stable anoxic basin [5]. Below 150 m, anoxic conditions begin and the oxygen content is limited, and this anoxic region encompasses 87% (5.3 x 105 km^3) of the total volume of the Black Sea [6]. The Black Sea, which is 353 km^3 y^{-1} total fresh water input from rivers, watershed includes 17 different countries. The five largest rivers are the Danube (203 km^3 y^{-1}), Dneiper (54 km^3 y^{-1}), Don (28 km^3 y^{-1}), Kuban (13 km^3 y^{-1}) and Dniesta (9.3 km^3 y^{-1}) [5]. Besides there are 28 km^3 $y^{-1}$of fresh water contributions from a large number of smaller rivers and streams flowing along the Turkish and Bulgarian coasts [7] and 17.7 km^3 $y^{-1}$of river water discharged into the remaining small rivers and streams located in the basin [5].

Particularly in Black Sea Region of Turkey, population density is in the coastal area due to the vacant land problem. Each outfall is characterized according to length (m), maximum depth (m), treatment levels such as untreated, pre-treated, primary treatment, secondary or better treatment, flow (m^3.day^{-1}) and organic matter mass discharged (kg.day^{-1}) [8]. Deep sea discharge, which is location 33 domestic deep sea discharges along the Black Sea coast of Turkey, is preferred for wastewater by municipalities because of the land issue [4]. This investigation is carried out for three of these 33 domestic deep sea discharges.

The deep sea discharge studies are regulated by a Turkish Water Pollution Control Regulation [9]. The permit issued by the Republic of Turkey Ministry of Environment and Urbanization. Quality standards are defined so as to preserve the beneficial use of the sea and its product. The determination of the water standards is very complex and their monitoring is strongly linked with water use [10]. Therefore, pathogens are a serious concern for managers of water resources because excessive amounts of fecal bacteria in sewage and urban runoff have been known to indicate an increased risk of pathogen-induced illness in humans [11]. It is known that a minor amount of coliforms would indicate the presence of other detrimental bacteria or viruses in the mussels. The coliforms are among the bacterial indicators to be monitored [10]. Total coliform (TC) is selected as target indicator organisms as they are present in the feces of humans/ warm-blooded animals and found in high concentrations in the discharged effluent [1]. Bacterial inactivation rate and the related T90 parameter (the time required to inactivate 90% of the coliform bacteria) are important parameters for predictive calculations of indicator bacteria [12].

Table 1. Name of deep sea discharge systems in Trabzon Province

No	Name of deep sea discharge line
1	Ortahisar-Moloz
2	Ortahisar-Değirmendere
3	Ortahisar-Havaalanı
4	Of
5	Çarşıbaşı
6	Arsin
7	Yomra
8	Sürmene
9	Vakfıkebir

In this study, the parameters, which affect total coliform were evaluated using Artificial Neural Network (ANN) model in the coastal Eastern Black Sea of Turkey. Trabzon has been chosen because of the maximum number deep sea discharge systems in the Black Sea Region and the population served by deep sea discharges is high (Table 1). In addition, they have only primary treatment before deep sea discharge in study area.

MATERIAL AND METHODS

In-situ measurements

This study was carried out in deep sea discharge systems in the Eastern Black Sea of Turkey in July 2015. The pH, dissolved oxygen (%), temperature, conductivity, salinity and depth were measured on site with conductivity-temperature-depth (CTD). The samples were collected from three domestic deep sea discharge systems in Trabzon. These outfalls were located in Trabzon Arsin, Trabzon Of and Trabzon Ortahisar (Moloz) domestic deep sea discharge systems. The first and end of the diffuser points of Moloz, Arsin and Of deep sea discharge systems are shown in Figure 1. The coordinates of selected deep sea discharge lines are given in Table 2. The characteristics of the deep sea discharge systems are presented in Table 3.

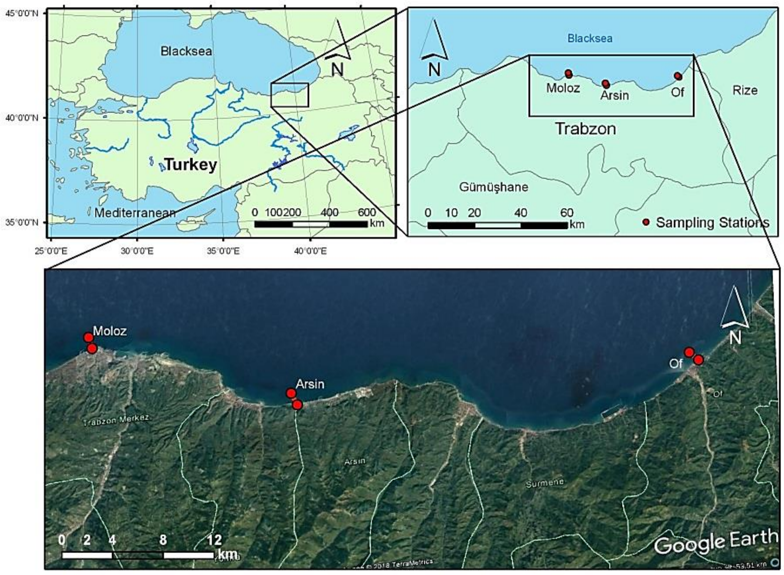

Figure 1. Locations of the sampling stations

Table 2. Coordinates for deep sea discharge lines

Station name	Coordinates	
Moloz	N41° 00' 44,28'	E39° 43' 01,52''
Arsin	N40° 57' 14,54'	E39° 54' 03,82''
Of	N40° 57' 10,57'	E40° 16' 33,39''

Table 3. Characteristics of deep sea discharge systems in sampling stations

Station	Flow ($m^3 \cdot d^{-1}$)	Total length of the line (m)	Diffuser output velocity ($m \cdot s^{-1}$)	Depth of discharge (m)	Treatment
Moloz	72922	800	4,2	45	Pre-treated
Arsin	3918,1	1036	3,73	34,6	Pre-treated
Of	7695,2	906	3,5	32	Pre-treated

Samples were taken to determine the stage of dilution of wastewater. Firstly, surface water samples were taken from approximately 0.5 m below the seawater surface at three deep sea discharges systems. In addition to surface samples, deep samples were collected from Trabzon Ortahisar deep sea discharge system due to high flow rate. Also, samples were taken from almost middle of seawater depths in Trabzon Ortahisar deep sea discharge system. All samples were collected from specified ten points for three domestic deep sea discharge systems. First point (N1) was described at the end of the discharge pipe. The next three points from the N1 were defined as a radius of 100 meters in order to determine the effect of near field dilution (N2, N3, N4). Four sampling points were determined as a radius of 500 meters in order to determine stage of dilution (N5, N6, N7, N8). The reference point (N9) was selected outside the 1000 meters of the discharge region. The last point (N10) was chosen from an area close nearly 300 meters to the shore (Figure 2). Coordinates for each sampling stations are given in Table 4.

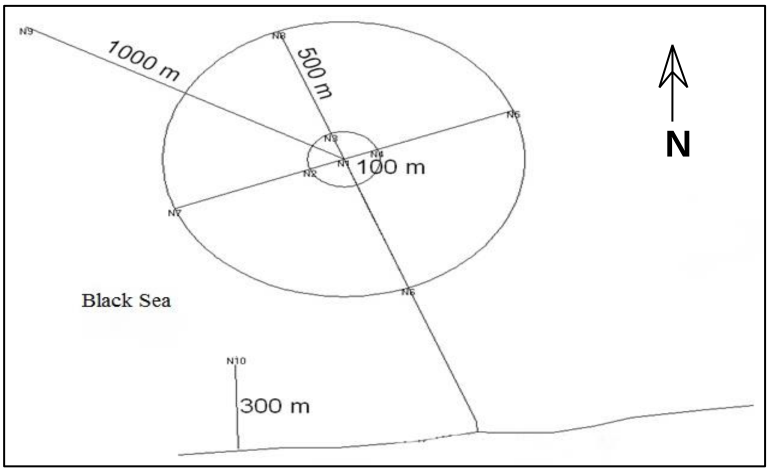

Figure 2. Location of deep sea discharge system in-situ measurement stations.

Table 4. Coordinates for each sampling stations

Station name	Coordinates					
	Arsin		Of		Moloz	
N1	N40° 57' 45,67'	E39° 53' 48,60''	N40° 57' 31,80'	E40° 16' 05,39''	N41° 01' 06,61'	E39° 42' 57,26''
N2	N40° 57' 44,54'	E39° 53' 44,59''	N40° 57' 29,49'	E40° 16' 02,40''	N41° 01' 06,16'	E39° 42' 53,03''
N3	N40° 57' 48,71'	E39° 53' 47,11''	N40° 57' 34,08'	E40° 16' 02,34''	N41° 01' 09,82'	E39° 42' 56,67''
N4	N40° 57' 46,80'	E39° 53' 52,61''	N40° 57' 34,11'	E40° 16' 08,39''	N41° 01' 07,05'	E39° 43' 01,50''
N5	N40° 57' 51,30'	E39° 54' 08,68''	N40° 57' 43,37'	E40° 16' 20,42''	N41° 01' 08,83'	E39° 43' 18,46''
N6	N40° 57' 30,49'	E39° 53' 56,05''	N40° 57' 20,46'	E40° 16' 20,66''	N41° 00' 55,02'	E39° 42' 59,43''
N7	N40° 57' 40,02'	E39° 53' 28,56''	N40° 57' 20,23'	E40° 15' 50,43''	N41° 01' 04,35'	E39° 42' 36,07''
N8	N40° 58' 00,87'	E39° 53' 41,16''	N40° 57' 43,16'	E40° 15' 50,14''	N41° 01' 22,66'	E39° 42' 54,30''
N9	N40° 58' 01,59'	E39° 53' 11,34''	N40° 57' 32,99'	E40° 15' 22,78''	N41° 01' 26,04'	E39° 42' 23,01''
N10	N40° 57' 28,46'	E39° 53' 33,89''	N40° 57' 09,60'	E40° 16' 05,22''	N41° 00' 48,92'	E39° 42' 39,09''

If reference sites or point are located too far from the outfall, the differences between seawater quality profiles resulting from natural variations could be confused with the impact of effluent, increasing the chance of false positives. On the contrary, reference sites or point located too close to the outfall can themselves be affected by wastewater and result in failure to detect plume impact [13]. Therefore, N9, which out of discharge area, was selected as a reference point.

Laboratory analysis

Seawater samples were collected at each of the sampling points from different water depths using a 5 L Niskin water sampler (Table 4). The laboratory studies were carried out according to the standard methods for the following parameters: Total suspended solids (TSS, APHA 2540D), biological oxygen demand (BOD, APHA 5210B), total coliform (TS EN ISO 9308-1), ammonia (SM 4500-NH3:B-C), mercury (SM 3112:B), arsenic (SM 3114:C), copper (SM 3111:B), cadmium (SM 3111:B), chromium (SM 3111:B), lead (SM 3111:B), nickel (SM 3111:B), zinc (SM 3111:B) and chlorophyll-a (TS 9092 ISO 10260) [14].

Artificial Neural Network (ANN)

The ANN model was trained using the database as the inputs and the corresponding measured pH, dissolved oxygen, temperature, salinity, biological oxygen demand, conductivity, total suspended solid, ammonia, chlorophyll-a and heavy metals were used as the outputs. In this research, ANN model consisted of 10 neurons in the input layer and in the output layer.

In the present study, 70% of the data set was selected as training data. The rest of the data set were used 15% for testing and 15% for validation (MSE) and maximum iteration number were set to 0.001 and 1000 epoch, respectively. Since the accuracy of estimation is highly dependent on covering all level of data, the randomization process was repeated until a satisfactory level of data distribution was reached.

The training process completed when all weighing indices were fixed and the ANN model can accurately estimate the output data as a function of input values [15]. The number of hidden layers (10 hidden layers) and the number of neurons in hidden layer were determined by the training error method. MATLAB (Matlab ® 7.11.0.584(R2010b)) was used for the artificial neural network. (train_fcn = 'trainbr'; train_tf = 'tansig'; for hn=2:5:10for epoch=50:150:450; net = newff (ds.train.X, ds.train.y, hn, {train_tf}, train_fcn).

RESULTS AND DISCUSSION

Artificial neural network (ANN) is a computational modeling tool that used to solve many complex real world problems due to its remarkable learning and generalization capabilities [8]. ANN is also non-linear data driven self-adaptive systems, and they can identify and learn correlated patterns between input data sets and corresponding target values, even when the underlying data relationship is unknown. Artificial neural networks have been widely used to model complex and nonlinear processes and systems [16].In a study, temperature, density, salinity, conductivity, dissolved oxygen, total coliform, total nitrogen and phosphorus were measured on samples taken from points at different depths in the Black Sea. The irregular and uncertain environment of the sea, which cannot be fully explained, causes the design parameters to change every minute and may lead to risks regarding the detection of forces due to nature parameters [17].

In this study, Levenberg-Marquardt (LM) and Bayesian Regularization Back-propagation (BRB) algorithm were used to train MLP network. MLP is a feed-forward neural network with one or more layers between input and output layer. Feed-forward means that data flow in one direction from input to output layer (forward). LM algorithm is originally an intermediate optimization algorithm between the Gauss–Newton (GN) method and Gradient Descent (GD) algorithm. It combines the speed of the Newton algorithm with the stability of the GD method. BRB algorithm is a network training function. This function minimizes a combination of squared errors and weights and updates the weight and bias values according to LM optimization. It produces well-generalized network by determining the correct combination of squared errors and weights.

ANNs can detect the important features of the input-output relationships with the help of nodes in the hidden layer. The hidden layer and nodes are very important for ANN. The nodes in the hidden layer capture the pattern in the data used. For many practical problems where we need to approximate any function that contains a continuous mapping from one finite space to another, there is no reason to use any more than one hidden layer. The number of neurons used was determined by trial and error. Transfer functions calculate a layer’s output from its net input. The function logsig generates outputs between 0 and 1 as the neuron’s net input goes from negative to positive infinity. Logsig function is generally used when the network is used for pattern recognition problems such as this.

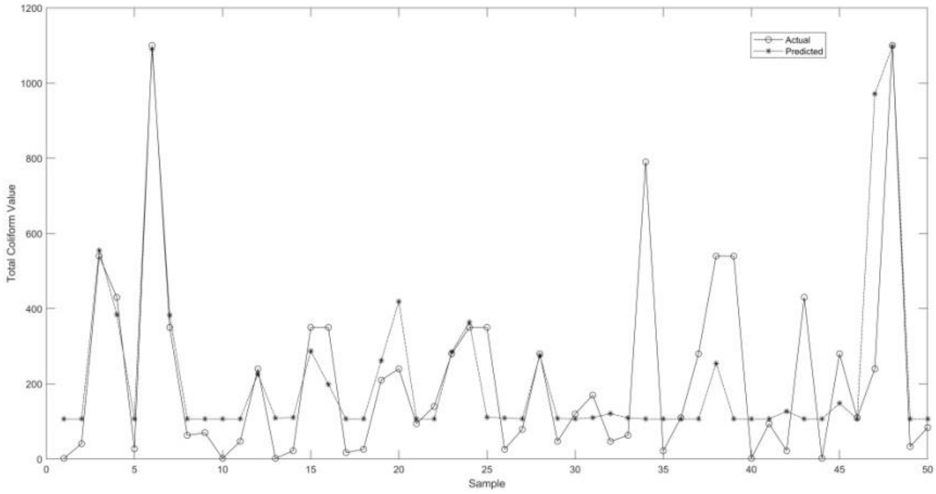

Figure 3. Comparison of actual and predicted total coliform values

The actual and predicted values produced for total coliform were compared using artificial neural network in Figure 3. In the Figure 3, "*" symbolizes the predicted values and "o" symbolizes the actual values. Total coliform values were predicted with high accuracy in both train and test dataset. The actual and predicted total coliform in seawater was estimated with higher accuracy.

According to Descriptive Statistics, Total Coliform Values are between 1.8 and 1100 (Table 5). Train, test and overall dataset's value averages are close to each other 199.61, 257.77 and 217.06, respectively.

Table 5. Descriptive statistics

		min	max	std	mean	median
Overall	**y**	1.80	1100.0	256.35	217.06	110.00
	yh	106.78	1097.7	237.37	217.69	107.33
Train	**y**	1.80	1100.0	239.31	199.61	94.00
	yh	106.78	1089.6	193.82	206.24	109.16
Test	**y**	1.80	1100.0	297.31	257.77	110.00
	yh	106.78	1097.7	323.83	244.42	106.80

* y actual and yh predicted total coliform value

Predetermined values for the output error (MSE) and maximum iteration number were set to 0.001 and 1000 epoch, respectively. Since the accuracy of estimation is highly dependent on covering all level of data, the randomization process was repeated until a satisfactory level of data distribution was reached. The training process will be completed when all weighing indices are fixed and the ANN model can accurately estimate the output data as a function of input values. Randomly chosen 70% of the data set was selected as training data for ANN model. The rest 30% of dataset was used for testing and validation. An output error of 0.185 MSE was determined for generated outputs by logsig transfer function with a maximum iteration number of 1000 epochs. Root Mean Squared Error (RMSE) values for train, test and overall dataset were obtained 140.84, 257.42 and 183.75, respectively (Table 6). Compatible with R^2 values corresponding to error values 0.80, 0.64 and 0.78, respectively (Figure 4).

Table 6. RMSE error metric

Dataset	RMSE	std
Train	140.84	142.74
Test	257.42	266.09
Overall	183.75	185.61

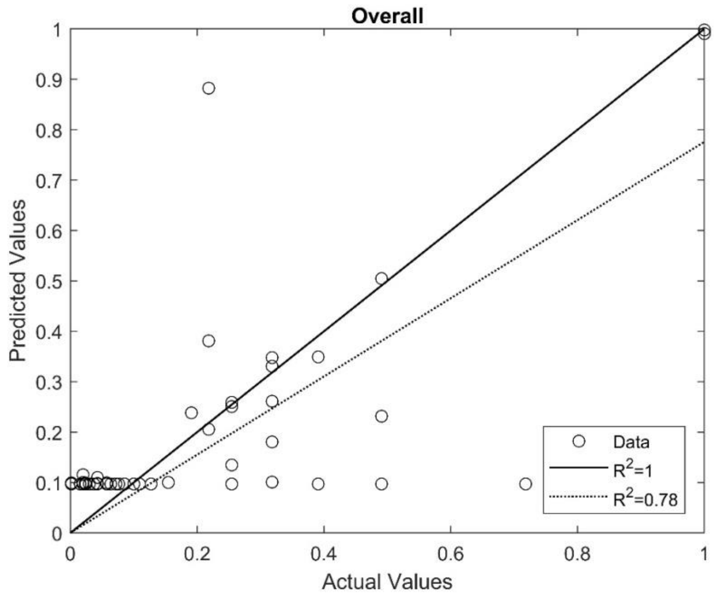

Figure 4. R^2 Performance of Artificial Neural Network

CONCLUSION

Deep sea discharge systems are preferred in order to benefit from the dilution capacity of marine environments due to the high population and the land problem of the wastewater treatment plant in the particularly Black Sea Region of Turkey. Trabzon, which is located Eastern Black Sea of Turkey, is also one of the provinces both a high population and the wastewater treatment plant land problem. Therefore, the present study is carried out at Trabzon Moloz, Trabzon Arsin and Trabzon Of domestic deep sea discharge systems, which have only primary treatment. Moreover, Trabzon Province is one of the most deep sea discharge systems in Turkey.

Deep sea discharge systems efficiency depends on the percentage of total coliform dilution that caused by the feces of humans/warm-blooded animals. Consequently, total coliform is regarded as a target indication of pollution in the seawater. The dilution and biochemical processes, which formed by the mixing of treated domestic wastewater discharge into marine environment with sea water, reduce the adverse effect of discharge wastewater. Because of the complex and dynamic nature of the marine environment, many parameters affect these processes. Dilution of total coliform is one of the most important design parameters of deep sea discharge systems in terms of marine environment. The concentration values of the pollutant parameters in the discharged wastewater are related with the dilution values of total coliform. The objective is to ensure that the concentrations of contaminants are below the acceptable levels of sufficient total dilution. In this study, total coliform values and other parameters related to total coliform were investigated in Trabzon Province of Turkey using ANN model.

ANN was adopted to obtain the model for predicting sea pollution and estimate the relationship between total coliform and other parameters. The coefficient of determination (R^2) was 0.78 and mean square error (MSE) was obtained 0.185 from validation.

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