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The Assessment of Effective Factors on Anzali Wetland Pollution Using Artificial Neural Networks

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Abstract: Anzali wetland, which is located in north part of Iran, is one of the most important ecosystems in the world considering economical and environmental features, and is in the list of Ramsar Convention. Receiving wastewater with minimum treatment caused increasing water pollution in the wetland. In this regard, having enough and accurate data and precise interpretation are necessary which may help water quality management. There are many methods for interpretation of data. In this work, prediction of COD parameter in Siakeshim station in south part of the wetland was studied using Artificial Neural Network (ANN) considering effects of five parameters TP, TN, (NO_3-N), (NO_2-N) and (NH_4-N) as the most important features of nutritional materials and creation of utrification and also predictors of pollution. The ten years average monthly data of five mentioned parameters are applied as input of Multi Layer Perception (MLP) models. The results of the study showed that using MLP methods obtained precise predictions for COD parameter and also the rate of effects of each input parameters in water pollution. Hence, prediction of water quality using ANN model may be useful for water quality planning and management.

Key words: Utrification, Anzali wetland, artificial neural network, multi layer perception.

Introduction

Lack of suitable wastewater treatment facilities causes municipal and industrial wastewater drain to the Anzali wetland without sufficient control. As a result, water pollution will be increased. Anzali wetland is one of the most important ecosystems considering economical and environmental features which have been in Montro Content by Ramsar Convention due to utrification phenomena (Akbarzadeh, 1995). Utrification is enrichment of nutrition in surface waters and negative effects on water quality and water ecosystems. Increasing amount of phosphor and nitrogen create conditions for hyper growth of plants. Utrification is a natural process and perhaps takes a long time to see the effects but this process will be accelerated by man and it is called human-made utrification. Nowadays, a threat for water quality and hygiene of human-made utrification is the result of increasing nutrition (N, P) which are drained into rivers, lakes and other water resources because of human activities. Pollution of Anzali wetland is considered as an important problem; therefore prediction and study of the amount of pollution is necessary for water quality management.

The ANN has been considered a useful and confident tool to modelling of complicated relationship during the recent decades. Applying the input and output in the ANN can estimate the relations between them and train in a way that ANN predicts the corresponding output member against a new input member. In the report of the American Society of Civil Engineering (ASCE) search committee, applying the ANN has been emphasized as a useful and

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worthy option in different hydrologic and environmental modelling. They investigated the role of ANN in different hydrologic and environmental branches and found that ANN is able to simulate many complicated nonlinear relationships (ASCE, 2000a, b). According to Universal Approximation, each MLP of ANN with a sigmoid hidden layer and a linear output layer is able to predict each complicated parameter if number of neurals are selected precisely (Hornik et al., 1989).

Christon et al. (2007) developed a model that could be applied for design of the undersurface horizontal wetlands. This model was developed based on the existing information from five units according to pilot measures using ANN models which were designed according to information of a two-year period and with four different hydraulic detention time. Initially, slight analyses were performed to find the appropriate input parameters to ANN models. As a result they found that the most important and effective parameters to BOD elimination are the amount of porosity in applying media, wastewater temperature and hydraulic detention time and a group of related parameters to metrology. Two artificial neural networks Radial Basis Function (RBF) and MLP were examined. The RBF network indicated favourable results on BOD elimination. But, the MLP network indicated better results. Karul et al. (2000) applied the ANN models in utrification. For indication of limitation and advantage of ANN models a case study for prediction of chlorophyll-a in Keban dam as a function of water quality parameters such as phosphate (PO_4), nitrate (NO_3), alkaline TDS, pH, water temperature, electrical conductivity, DO, and depth of Secchi was developed using the ANN models. They compared their results with traditional linear regression analysis and found good agreement between two methods.

Anzali wetland is located in south of Caspian Sea in Ghelan province in north of Iran and its geographic coordinates are 28°37′ North latitude and 25°37′ East longitude. Total area is 150 square kilometre. The average length of the wetland in East-West direction is about 30 km and North-South direction is about 3 km. Figure 1 shows the map of the wetland. Table 1 shows statistical summary of Anzali wetland water quality data.

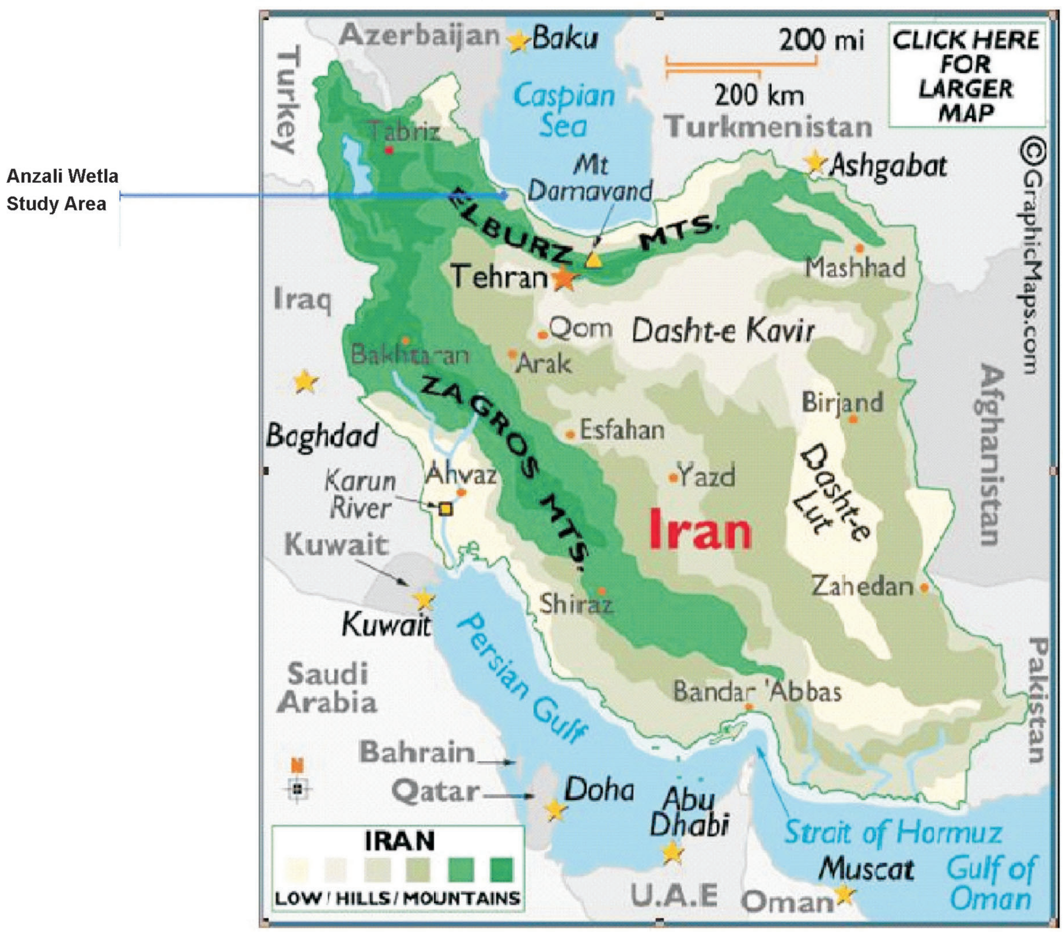

Figure 1: Location of water quality monitoring station in Siakeshim.

Table 1: Statistical summary of Anzali wetland water quality data

Parameters	*Count*	*Mean*	*Min*	*10th percentile*	*25th percentile*	*50th percentile*	*70th percentile*	*90th percentile*	*Max*	*St. dev.*
TP	120	0.174	0.03	0.06	0.09	0.71	0.22	0.32	0.42	0.098
NO_3-N	120	0.690	0.15	0.4	0.55	0.7	.835	0.984	1.3	0.218
NO_2-N	120	0.018	0.01	0.01	0.01	0.013	0.02	0.03	0.06	0.010
NH_4-N	120	0.947	0.12	0.658	0.8	0.91	1.05	1.25	1.85	0.266
TN	120	2.168	0.29	1.39	1.795	2.41	2.5	2.908	4.12	0.616
COD	120	32.86667	11	14.8	20	28	40	58.2	91	17.3647

TP: Total Phosphor, NO_3-N: Nitrate nitrogen, NO_2-N: Nitrite nitrogen, NH_4-N: Ammonia nitrogen, TN: Total nitrogen, COD: Chemical oxygen demand. All units are mg/L.

The objective of this study is applying the MLP models to 10 years average monthly water quality data which include TP, TN, (NO_3-N), (NO_2-N), (NH_4-N) and COD in Siakeshim water quality monitoring station in south area of the wetland. In this work, authors will try to show effectiveness of first five mentioned parameters with one month delay as a predictors of COD and utrification using MLP model.

Methodology

The ANN

Considering natural neuron and its components, scientists developed artificial neuron which is a smallest processing unit of an ANN. An artificial neuron consists of three components which contains weighing (w), bias (b) and transfer function (f). These three components for each neuron is unique. Figure 2 shows schematic of artificial neuron. In this figure p and a are input and output of a neuron, respectively. Parameter n is called net input, which is input of transfer function and it is built according to input p and neuron parameters. Mentioned artificial neuron can be modelled by following equations.

$$n = wp+b \qquad (1)$$

$$a = f(n) = f(wp+b) \qquad (2)$$

In neuron instruction process, w and b parameters should change step by step until it is obtained the best approximation for similar output member which is applied to input of the system. Weighing neuron determines the rate of effect of p over a, and parameter b causes that neuron is transformed to sub space of bias input space. Some types of transfer functions are as follows:

- linear, transfer function,
- hard-limit transfer function,
- log-Sigmoid transfer function,
- tan-Sigmoid transfer function, and
- tan-hyperbolic transfer function.

In general, there are two types of artificial neuron network models:

- static model and
- dynamic model.

According to mentioned theory all ANN which are applied in this research are MLP with a hidden layer (Figure 3), tangent sigmoid transfer function and linear layer outputs. Figures 4 and 5 show schematic tangent-sigmoid transfer function and linear transfer function for output layers respectively. Number of neurons in hidden layers for each model may be obtained using trial and error method. MLP with a hidden layer, tangent sigmoid transfer function and linear layer outputs can be modelled by equations 3 and 4:

$$a_j^1(t) = F\left\{\Sigma_{i=1}^{R} w_{j,i}^1 p_i(t) + b_j^1\right\} \qquad (3)$$

$$a_k^2(t) = G\left\{\Sigma_{j=1}^{s1} w_{kj}^2 a_j^1(t) + b_k^2\right\} \qquad (4)$$

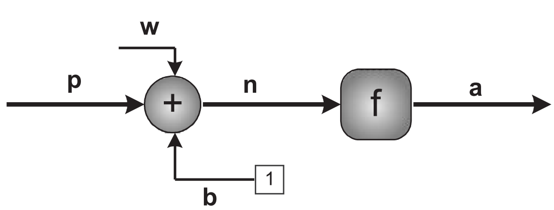

Figure 2: Schematic of an artificial neuron.

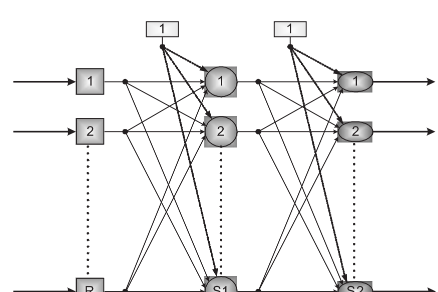

Figure 3: Schematic of MLP with a hidden layer.

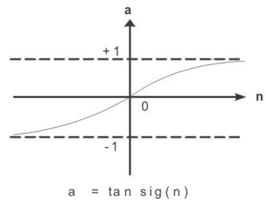

Figure 4: Transfer function tangent Sigmond.

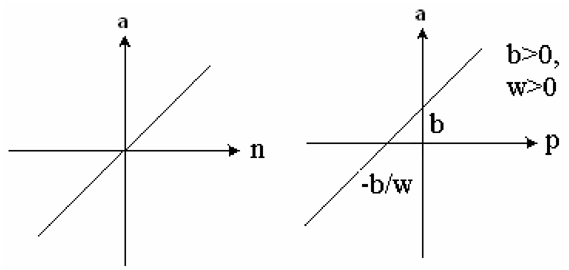

Figure 5: Linear transfer function.

In equations 3 and 4 R is number of input vector components, S_1 and S_2 are numbers of neurons in hidden and output layers, respectively. P is input vector. w^1 and w^2 are weighting matrix in hidden and output layers, respectively. b^1 and b^2 are bias vectors in hidden and output layers, respectively. G and F are neuron transfer functions in hidden and output layers respectively.

Figure 3 shows the schematic of the ANN. According to the mentioned theory all ANN which are applied in this research are MLP with a hidden layer, tangent sigmoid transfer function and linear layer outputs. Figures 3 and 4 show schematic tangent-sigmoid transfer function and linear transfer function. Number of neurals in hidden layers for each model may be obtained using trial and error. Generally there are two types of artificial neural network models as static model and dynamic model. In static model time is not considered and outputs of network at any time depend on the inputs at the same time.

To assess accuracy of the models applied in this research, the Variance Error (VE) is used which is obtained from the equation 5.

$$\mathrm{VE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Obs_t - For_t}{Obs_t}\right| \times 100 \tag{5}$$

Parameters of the equation are:

t—discrete time, T—length of time series, Obs_t—observed parameter in time of t ($1 \le t \le T$), and For_t—predicted parameter in time of t ($1 \le t \le T$).

Also the correlation coefficient (R) is applied to show the validity between real data and predicted ones which are described in equation 6

$$R = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}} \tag{6}$$

Results

The objective of this study, as mentioned previously, is analyzing and prediction of water pollution (COD) in a station in southern part of Anzali wetland (Siakeshim area) with having existing data for TP, TN, (NO_3-N), (NO_2-N) and (NH_4-N) parameters using ANN method. MLP model with ten years existing data out of which four recent years were applied for testing the models and the remaining years for training them.

Regarding the universal approximation theory all ANN models used in this work have similar structures and the differences are between the number of neurals in hidden layer.

The results of MLP prediction applying TP, TN, (NO_2-N) and (NH_4-N) parameters and time delay of one month would be mentioned separately. MATLAB software version 2007b and Neural Network have been applied for data analyzing.

Results of COD Prediction Using TP Parameter

Table 2 shows COD prediction errors using TP as input parameter of the MLP model. It is applied 2 to 10 neurons in hidden layer of considered network.

Figures 6, 7 and 8 indicate variation errors percentage via increasing of neuron numbers in hidden layer in training, testing and total respectively. As it is shown in the figures the minimum error is obtained when three neurals in the hidden layer are applied. Selecting the range of 2 to 10 neurals in the hidden layer is based on trial and errors. As it is shown in Table 2, increasing the number

Table 2: COD prediction errors percentage using TP parameter as input of the MLP model

Number of neurons	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Training VE%	11.14771	8.297555	11.92574	21.29326	11.18106	15.57139	44.56211	43.49595	43.72732
Test VE%	10.85887	8.222669	11.63488	21.20939	10.89213	15.27105	56.75925	51.97.69	52.50479
Total VE%	11.13148	8.293348	11.9094	21.28855	11.16482	15.55452	45.24735	43.97206	44.22043

of neural toward 10, the rate of errors is increased. This may indicate that increasing the excessive neural causes excessive complications in considered network. Figure 9 shows the predicted and actual COD parameter variations during 10 years. The high conformity of the figures (Figure 9) shows reasonable accuracy in predicting COD using TP parameter as input of MLP. Correlation coefficients in training, testing and total periods between predicted and actual data are 0.942, 0.963 and 0.915 respectively which shows that there is good accuracy in this work.

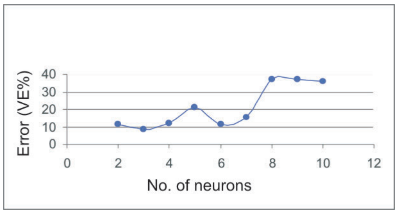

Figure 6: Variation errors percentage via neuron numbers in hidden layer (training period).

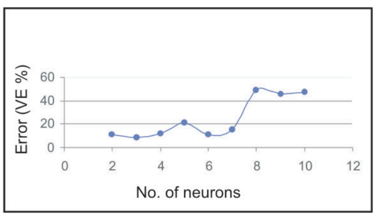

Figure 7: Variation errors percentage via neuron numbers in hidden layer (test period).

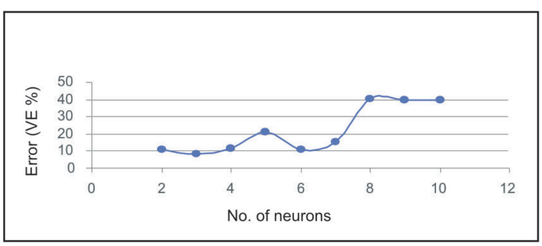

Figure 8: Variations error percentage via neuron numbers in hidden layer (total).

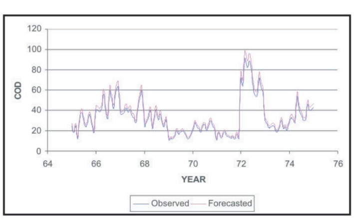

Figure 9: Time series of actual and predicted COD.

Results of COD Prediction Using TN Parameter

Table 3 shows COD prediction errors using TN as input parameter of the MLP model. It is applied 2 to 10 neurons in hidden layer of considered network.

Figures 10, 11 and 12 indicate variation errors percentage via increasing of neuron numbers in hidden layer in training, testing and total, respectively. As it is shown in the figures the minimum error is obtained when three neurals in the hidden layer are applied. Selecting

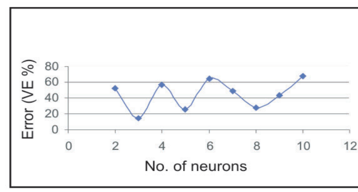

Figure 10: Variation errors percentage via neuron numbers in hidden layer (training period).

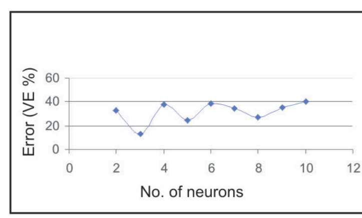

Figure 11: Variation errors percentage via neuron numbers in hidden layer (test period).

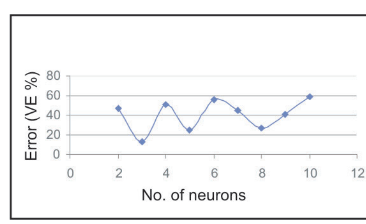

Figure 12: Variation errors percentage via neuron numbers in hidden layer (total).

Table 3: COD prediction errors percentage using TN parameter as input of the MLP model

Number of neurons	2	3	4	5	6	7	8	9	10
Training VE%	53.3183	13.3067	60.5092	25.7510	68.3492	53.2871	27.2335	46.9157	72.3914
Test VE%	43.9569	13.3518	48.1912	25.2205	53.0302	43.0977	27.0673	39.8445	55.6665
Total VE%	52.9918	13.3518	60.0795	25.7325	67.8148	52.9317	27.2277	46.6691	71.8079

the range of 2 to 10 neurals in the hidden layer is based on trial and error as mentioned previously.

Figure 13 shows variations of predicted and actual data during 10 years using TN as input to the MLP model. The high conformity of the figures (Figure 13) shows reasonable accuracy in predicting COD using TP parameter as input of MLP model. Correlation coefficients in training, testing and total periods between predicted and actual data are 0.992, 0.963, and 0.997 respectively which shows that there is good accuracy in this work.

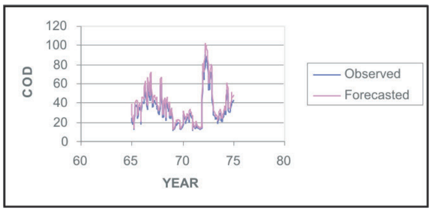

Figure 13: Time series of actual and predicted COD using TN parameter.

Results of COD Prediction Using NO_3-N Parameter

Table 4 shows COD prediction errors using NO_3-N as input parameter of the MLP model. It is applied 2 to 10 neurons in hidden layer of considered network.

Figures 14 and 15 indicate variation errors percentage via increasing of neuron numbers in hidden layer in training, testing and total, respectively. As it is shown in the figures the minimum error is obtained when ten neurals in the hidden layer are applied.

Figure 16 shows variations of predicted and actual data during 10 years using NO_3-N as input to the MLP model. The high conformity of the figures (Figure 16) shows reasonable accuracy in predicting COD using NO_3-N parameter as input of MLP model. Correlation coefficients in training, testing and total periods between predicted and actual data are 0.972, 0.994 and 0.984 respectively which shows that there is good accuracy in this work.

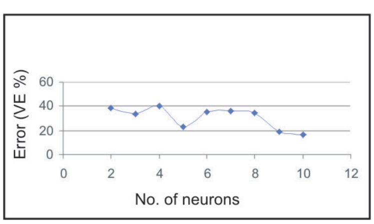

Figure 14: Variation errors percentage via neuron numbers in hidden layer (test period).

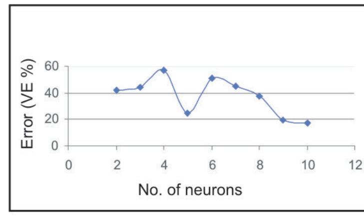

Figure 15: Variation errors percentage via neuron numbers in hidden layer (total).

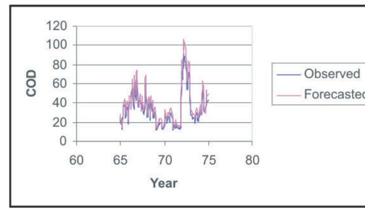

Figure 16: Time series of actual and predicted COD using NO_3-N parameter.

Results of COD Prediction Using NO_2-N Parameter

Table 5 shows COD prediction errors using NO_2-N as input parameter of the MLP model. It is applied 2 to 10 neurons in hidden layer of considered network.

Figures 17, 18 and 19 indicate variation errors percentage via increasing of neuron numbers in hidden layer in training, testing and total, respectively. As it is shown in the figures the minimum error is obtained when nine neurals in the hidden layer are applied.

Figure 20 shows variations of predicted and actual data during 10 years using NO_2-N as input to the MLP model. The high conformity of the figures (Figure 20) shows reasonable accuracy in predicting COD using NO_2-N parameter as input of MLP model. Correlation coefficients in training, testing and total periods between predicted and actual data are 0.942, 0.963 and 0.915 respectively which shows that there is good accuracy.

Table 4: COD prediction errors percentage using NO_3-N parameter as input of the MLP

Number of neurons	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Training VE%	43.738	49.579	67.777	26.019	59.698	52.762	39.009	20.239	17.012
Test VE%	41.1793	42.4810	53.5926	24.5513	47.7703	43.364	36.6240	19.5163	16.755
Total VE%	43.6498	49.3343	67.2883	25.9692	59.2869	52.438	38.9273	20.2148	17.003

Table 5: COD prediction errors percentage using NO_2-N parameter as input of the MLP

Number of neurons	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Training VE%	76.5579	55.6906	36.8700	68.5010	60.3819	82.1014	55.2131	24.1534	28.4779
Test VE%	45.3615	38.5755	36.4085	42.4654	39.8286	49.3935	38.4957	24.0356	28.0446
Total VE%	75.1399	54.9126	36.8491	67.3176	59.4476	80.6147	54.4532	24.1481	28.4582

Table 6: COD prediction errors percentage using NH_4-N parameter as input of the MLP

Number of neurons	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Training VE%	67.624	48.356	32.048	27.163	86.188	24.661	51.549	75.499	20.446
Test VE%	52.651	47.316	31.122	26.483	66.972	23.996	42.230	58.663	19.802
Total VE%	67.108	48.320	32.016	27.140	85.525	24.638	51.228	74.918	20.423

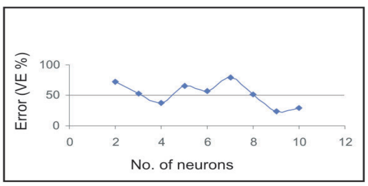

Figure 17: Variation errors percentage via neuron numbers in hidden layer (training period).

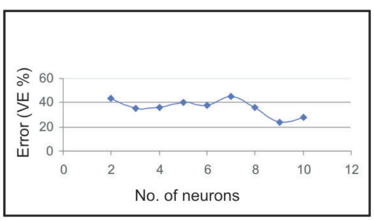

Figure 18: Variation errors percentage via neuron numbers in hidden layer (testing period).

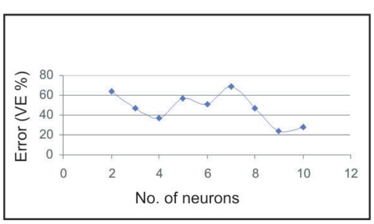

Figure 19: Variation errors percentage via neuron numbers in hidden layer (total).

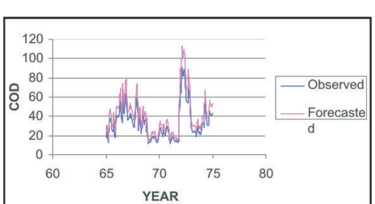

Figure 20: Time series of actual and predicted COD using NO_2-N parameter.

Results of COD Prediction Using NH_4-N Parameter

Table 6 shows COD prediction errors using NH_4-N as input parameter of the MLP model. It is applied 2 to 10 neurons in hidden layer of considered network.

Figures 21, 22 and 23 indicate variation errors percentage via increasing of neuron numbers in hidden layer in training, testing and total, respectively. As it is shown in the figures the minimum error is obtained when ten neurals in the hidden layer are applied.

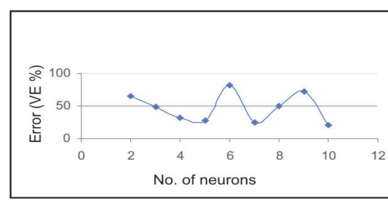

Figure 21: Variation errors percentage via neuron numbers in hidden layer (training period).

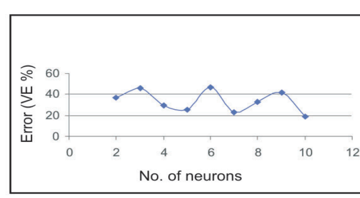

Figure 22: Variation errors percentage via neuron numbers in hidden layer (testing period).

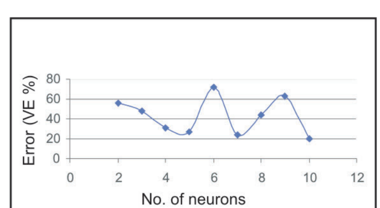

Figure 23: Variation errors percentage via neuron numbers in hidden layer (total).

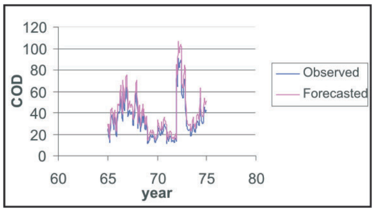

Figure 24: Time series of predicted and real COD applying (NH_4-N) parameter.

Figure 24 shows variations of predicted and actual data during 10 years using NH_4-N as input to the MLP model. The high conformity of the figures (Figure 24) shows reasonable accuracy in predicting COD using NH_4-N parameter as input of MLP model. Correlation coefficients in training, testing and total periods between predicted and actual data are 0.942, 0.963 and 0.915 respectively which shows that there is good accuracy.

Conclusion

The applied MLP model has a good capability to predict COD of the study area and as observed TP, TN, (NO_3-N), (NH_4-N) and (NO_2-N) parameters may be proper predictors to estimate COD parameter, respectively and they are most effective on the wetland pollution (COD), but as a total all the parameters have acceptable errors and correlation coefficients.

TP, TN, (NO_3-N), (NH_4-N) and (NO_2-N) resulted in greater errors in predicting pollution rate respectively. This fact may indicate that the more the parameters are involved, the less the error and the more their oxygen reduction will be.

TP parameter has the lowest error which was 8.22% using three neurons in the hidden layer and also correlation coefficients in the training, testing and total periods were 0.942, 0.963 and 0.915 respectively. All these results may show the accuracy of predicted model and also indicate that TP parameter has more involvement than other parameters in generating pollution.

NO_2-N parameter has the biggest error which was 24.03% using nine neurons in the hidden layer and also correlation coefficients in the training, testing and total periods were 0.942, 0.963 and 0.915 respectively. All these results may show the accuracy of predicted model and also may indicate that NO_2-N parameter has less involvement than other parameters in generating pollution.

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