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Using Algorithm (*Levenberg marquardt*) as Activation Function to Prediction Water Quality Index (WQI) in Kastamonu City-Turkey

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ANN, Karaçomak dam ,Water Quality Index.

ABSTRACT

The computer program of artificial neural network (ANN) to prediction the water quality index (WQI) at Municipality Water of Kastamonu City-Turkey. WQI demonstrates the overall water quality at a specific site and specific time depending on some water quality factors for 5 years (from Jan 2011 to Dec 2015). The simple feedforward network is applied with one of the training algorithms the standard back-propagation algorithm (Levenberg-Marquardt) (train-lm). In this study, one hidden layer has been selected for modelling and the number of the hidden neuron is set (n+1) and (2n+1) of input nodes. This discovering can be depicted by using the way that the quantity of hidden neurons straightforwardly affects the execution of the system and we can see that model the standard back-propagation algorithm (Levenberg-Marquardt) train-lm as activation function (train-Lm) is optimal to predict of water quality index and as more direct and very effective options to predict surface water quality and other water bodies.

الملخص العربي

استخدام الشبكة العصبية الاصطناعية (ANN) برنامج كمبيوتر) لاجراء تنبؤ (توقع) لمؤشر جودة المياه (WQI) في مدينة كاستامونا - تركيا. مؤشر جودة المياه يعطي وصف كامل لجودة المياه ضمن موقع محدد ووقت محدد اعتمادا علي بعض عوامل جودة المياه تمت خلال خمس سنوات (من يناير 2011 حتي ديسمبر 2015) طبقت شبكة التغذية المباشرة البسيطة باستخدام خوارزمية الانتشار الخلفي القياسية (train-Lm) (Levenberg-Marquardt) في النموذج. في هذه الدراسة ، تم استخدام طبقة مخفية واحدة للنمذجة مع عدد مختلف من الخلايا العصبية المخفية (n+ 1) و (2n+ 1) من عقد الإدخال. كشفت الدراسة التاثير المباشر لكمية الخلايا العصبية المخفية علي أداء النموذج ويمكننا أن نرى هذا النموذج لخوارزمية الانتشار الخلفي القياسية (Levenberg-Marquardt) كدالة تنشيط (train-Lm)هي الأمثل في الأداء للتنبؤ بمؤشر جودة المياه (WQI) مع خيارات فعالة للتنبؤ بجودة المياه السطحية وغيرها من المسطحات

INTRODUCTION

Water source programs all-around the world have become stressed in recent years. In Turkey the main attempts have been done in the 20th century to build the country's water supplies. because of a mix of some factors including fast population growth, increased per capita water consumption, the effects of climate change , the accompanying industrial, commercial and agricultural development (Bayazit & Avci, 1997). This kind of activity is making several potential sources of pollutants from organic and man-made fertilizers, landfill sites, accidental spills and domestic or industrial effluent discharges. For example, an agriculture-related actions are widely recognized non-point source pollution(Almasri & Kaluarachchi, 2005; Yesilnacar, Sahinkaya, Naz, & Ozkaya, 2008). Deterioration of water quality has waste disposal directly or not directly through started severe management attempts in many countries. The absolute most fitting ecological and water associated decisions are complicated to create without careful modeling, prediction and analysis of water quality for typical development scenarios(Faruk, 2010; Heydari, Olyaie, Mohebzadeh, & Kisi, 2013). The water quality management has an essential factor in water pollution manage and watershed planning. In spite of this, water pollution mainly occurs due to the overloading of waste in the water system. The pollution of rivers, lakes, underground water, bays or oceans by substances can be harmful to living things, not only human, but to the wildlife and plants(Najah, Elshafie, Karim, & Jaffar, 2009; Nasir et al., 2011). This is exactly why, a mathematical application used to transform physic-chemical water characterization data into a single number, which represents the water quality range called water quality index (WQI). That it utilizing this index will offer significant information to decision makers as to whether it is a benchmark-success or failure(Imneisi & Aydin, 2016). Nowadays, mathematical, statistical and computational methods to simulate and evaluate many water quality parameters have been investigated(Moasheri, Khammar, Poornoori, Beyranvand, & Soleimani, 2013; Nasr & Zahran, 2014). The prediction of water quality is an important step of the water environment management, is to investigate the regularity for the predicted index with the time using some predicting methods, and to understand the development pattern of the water environmental quality according to the history data. At present the prediction methods commonly used in water quality include the multiple linear regression(Manoj & Padhy, 2014; Qiuhua et al., 2014), the mathematical model of the water quality(Tyagi, Sharma, Singh, & Dobhal, 2013; Yisa & Jimoh, 2010), the neural network(Rooki, Ardejani, Aryafar, & Asadi, 2011; YUAN, GONG, ZHANG, & WANG, 2013). ANN models are such 'black box' models with specific characteristics which are significantly suitable to dynamic nonlinear system modeling. Artificial neural networks (ANNs) have been successfully utilized in the number of studies focusing on water quality prediction in rivers(Banejad & Olyaie, 2011; Khalil, Awadallah, Karaman, & El-Sayed, 2012), lakes(Panda, Garg, & Chaubey, 2004), reservoirs (Abdolmaleki, Ahangar, & Soltani, 2013) and water distribution systems(May, Dandy, Maier, & Nixon, 2008). (Erturk et al., 2010) modeled Water quality assessment using ANN in Melen watershed –Turkey. In this study the neural network models of ANN are used to prediction the WQI of Karaçomak Dam at intake of Kastamonu –Turkey.

MATERIALS AND METHODS

Study Site.

The study area is the major source of drinking water for the Kastamonu area where can be found (DSI). Table 1. Which show the all datasets for observation in the kastamonu city(DSI) before and after treatment.

Table 1. shows the all datasets for observation in the kastamonu city(DSI).

Information of sampling site	
Sampling stations	Station before and after treatment station.
Duration of study	From 2011 to 2015 every month
The number of samples	141

Geographically, the (DSI) is located at latitudes (41°39' 74.91" N), and longitudes (33° 78' 57.09"E) in the Kastamonu city, Turkey, and elevated 887 m above sea level. Sampling Stations were located on the (DSI) kastamonu city that shows in "Fig.1".

The study area is the main source of drinking water for Kastamonu area where exist near the

Karaçomak dam. That is one of the biggest dams in Turkey and it has some reason for using of irrigation and drinking water and control of flood in the area. Also, provided that an area of 9 million cubic meters of drinking water per year. Daily, 25 thousand tons of drinking water supplied from the dam Kastamonu Municipal Water Treatment is given monthly 750 thousand tons of drinking water.

"Fig.1". location of water municipality in the (DSI) kastamonu city – Turkey

Water Quality Data Source.

The different Water Quality (WQ) data set was collected from the Department of municipality water of Kastamonu city for two types of stations. first that, before primary treatment and second station (after treatment) which holds regular monitoring of the quality of intake water station during 12 months in every year since January 2011 to December 2016. This stations are located a few kilometers from Karaçomak Dam, and have been included in the Turkish's water quality monitoring program. Among the variables measured by the Department of municipality water of Kastamonu city are conductivity (EC), pH, phosphorus (PO4-P), water temperature (T), ammonia (NH4-N), nitrite (NO2-N), nitrate (NO3-N), Chloride (Cl), Iron(Fe), manganese (Mn), sulphate (SO4), Turbidity (NUT)and (Ka-WQI). Therefore, these thirteen parameters are included in model development. In brief, the rating of water quality according to this WQI is given in table 2. (Asuquo & Etim, 2012; Chatterjee & Raziuddin, 2002).

Table 2. Water quality rating as per weighted arithmetic water quality index.

WQI Value	Rating of water quality	Grading
0 - 25	Excellent water quality	A
26 - 50	Good water quality	B
51 - 75	Poor water quality	C
76 - 100	Very poor water quality	D
Above 100	Un-suitable for drinking purpose	E

The statistics of the variables are listed in Table 3. where minimum, maximum, and the mean factors. This dataset comprised 1833 data points derived from 13 measurements on 141 samples. Water quality data stored in excel (2008) format and linked with Matlab (2014a) program.

Table 3. The statistics of the variables of municipality water of Kastamonu city of stations (before and after treatment) (2011-2015).

Descriptive Statistics the Physical-Chemical Characteristics of Water at kastamonu city between (2011-2015)							
		Before treatment			After treatment		
N	variables	Min	Max	Mean	Min	Max	Mean
1	EC	402	486	436.	404.	495.	438.9
2	pH	7.49	8.62	8.04	7.70	8.32	8.00
3	Tempera	8.70	20.0	17.4	5.00	20.3	17.35
4	Turbidity	.82	10.6	3.45	.20	1.16	.5437
5	Cl	2.70	4.70	3.56	2.90	6.70	4.57
6	NH4	.00	.09	.031	.00	.08	.0260
7	NO3	.00	.50	.060	.00	.50	.0600
8	NO2	.00	.02	.004	.00	.05	.0040
9	PO4-P	.01	.23	.052	.00	.11	.0331
10	SO4	19.0	27.0	23.0	20.0	27.0	23.7
11	Fe	.01	.17	.047	.01	.20	.0233
12	Mn	.01	.21	.051	.01	.18	.0262
13	WQI	25.6	36.1	32.0	13.8	22.8	17.93

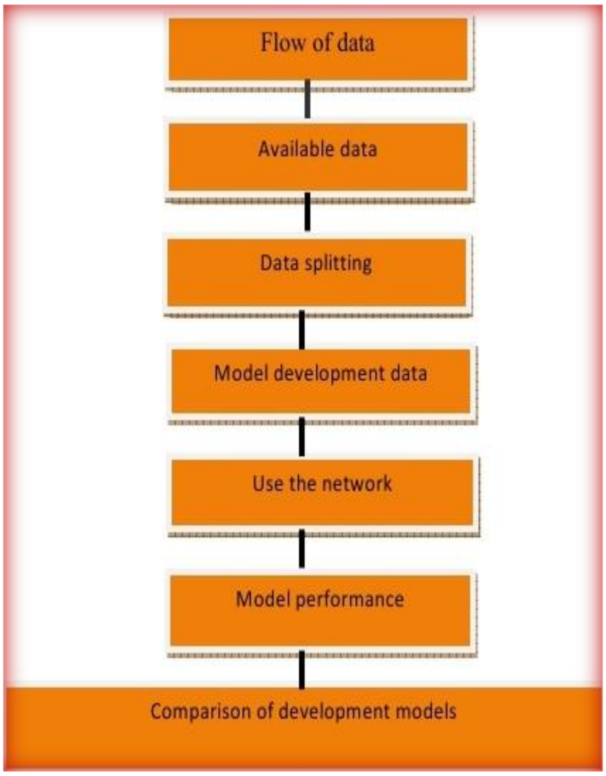
All variable the Unit of measurement parameters are (mg/l) except EC(µS/m) ,PH , Turbidity (NTU)and temperature .

Modeling of Water Quality Index Using an Artificial Neural Network.

1.The general introduction.

ANN models are such 'black box' models with specific characteristics which are significantly fitted to important nonlinear system modeling

(Daliakopoulos, Coulibaly, & Tsanis, 2005). According to (Jakeman, Letcher, & Norton, 2006) development of Artificial neural network model covered of the full technological process which are the 10 steps including formulating a hypothesis, collecting appropriate observations, data and a review of the hypothesis. The major steps in the development of ANN prediction models, and likewise the way the data flow through, and the results obtained at, various steps, are given in "Fig.2".



"Fig.2". The major steps in the development of ANN prediction models

2. Data pre-processing.

In almost any model development system, understanding the available data is of the great importance. ANN models are no exception to this rule and data preprocessing can have an important effect on model performance (Kaastra & Boyd, 1995; Maier & Dandy, 2000; Zhang & Stanley, 1997). Data standardization (scaling) is often done before the training steps should begin for high-speed unity, to avoid untimely filing of hidden nodes which is responsible for impeding the training process, and to predict the output in a manner fitting the functioning of the network(Sakthivel, Ravichandran, & Alagumurthi, 2016). The first dataset (input and output) proportionate to a matrix of 141 samples by 13 variables, then statistical outliers and structural zeros were retained, and the inputs variable and output were standardized to the range of the logistic sigmoid transfer (activation function), which include (0, 1).

In this study, the input values and output value were normalized from 0 to 1 using the basic formula for normalization to the range (a,b) given in "(1)". by(Gazzaz et al., 2012; Srinivasan, Dipti Liew, & AC Chang, 1994).

$$\mathbf{X_s} = \left[(\mathbf{b} - \mathbf{a}) * \frac{\mathbf{X_a} - \mathbf{X_{min}}}{\mathbf{X_{max}} - \mathbf{X_{min}}}\right] + \mathbf{a} \qquad "(\mathbf{1})"$$

Where X_s and X_a express the normalized and actual of variables X, respectively; a and b represent (0 and 1) the lower and upper limits of the standardization; and X_{max}, X_{min} refer to the minimum and maximum values of variables X, respectively.

3.Data splitting.

In the beginning part of the ANN model development plan is the choice of appropriate model output (s) (i.e. the variable (s) to be predicted and a set of probability model input parameters from the available data. According to (Maier, Jain, Dandy, & Sudheer, 2010; Wu, Dandy, & Maier, 2014). In most of the researchers can be done based on a priori knowledge and/or the availability of data that is more significant attention should be paid to the input variable selection step in the development process of ANN models. In this research, two different types of ANNs models were developed based on trial and error to choose a suitable model representation based on expert knowledge. Two datasets were utilized for training and testing using ANN-models. Are given in Table 4. Type of models using for prediction WQI.

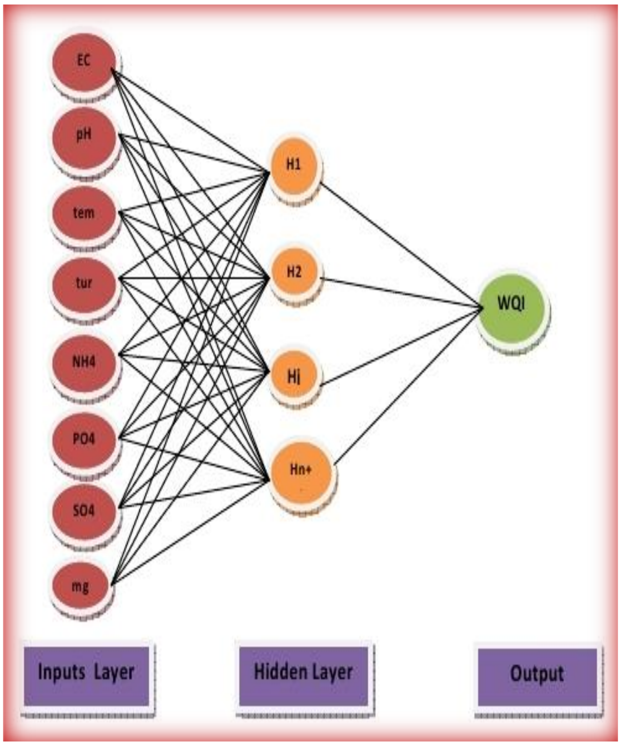
Table 4. Type of Kastamonu city-model using for prediction WQI.

Model area	Name of model	Training function	Network topography	Number of datasets	Input variables	Output variable
Kastamonu city-model	model-alm	Train-lm	(12,13,1)	141		WQI

	model-alm	Train-lm	(12,25,1)	141	All variables	WQI
	model-4lm	Train-lm	(4,5,1)	141	(NH4-N), (Fe), (PO4). (Mn)	WQI
	model-4lm	Train-lm	(4,9,1)	141		WQI

4.selection of model

The total 141 data set was split at random into three groups the first group of data was used the training set which represented 70% of the raw data. In addition, 98 sets of data were used as the testing set representing 15% of the raw data and 21 sets for validation which represented 15% of the data. This division of training and testing data is the one that is usually recommended. Which means that ANN models were carried out by using the samples after normalization values. In fact, feedforward neural networks have been used effectively in many types of issues as the advent of the error backpropagation learning algorithm. This network structure and the corresponding learning algorithm can be looked at a generalization of the popular least-mean-square (LMS) algorithm (Daliakopoulos et al., 2005) However, many researchers have been successfully using it (Chaipimonplin, 2016; SUJANA, VERMA, & SHWETA, 2015). Table 3. shows the final ANN architecture applied in this study which is based on a simple feedforward network. The network used consists of three layers, the input layer, the hidden layer with a two type of the number of hidden neurons, and the output layer with a single neuron. In this study, the simple feedforward network is applied with the standard back-propagation algorithm (Levenberg-Marquardt backpropagation) train-lm function that updates weight and bias values according to Levenberg-Marquardt optimization. The LM algorithm such as the quasi-Newton methods was developed to approach second-order training speed without obtaining to calculate the Hessian matrix. The LM algorithm has been found to be the fastest method for training an average-sized feedforward neural networks, although it needs a greater amount of memory than other algorithms(Karul, Soyupak, Çilesiz, Akbay, & Germen, 2000) For this reason, the Levenberg-Marquardt backpropagation algorithm had been determined which one was able to obtain the best performance as well as faster predictions in this research. In contrast, Structure of neural network comprises of three layers, which contains an input layer, a hidden layer, and an output layer that was given in “Fig.3”.



“Fig.3” Structure of neural network comprises of three layers.

Consequently, the good goal of the neural network model is to maximize the speed at which the network converges to a solution and the accuracy of its prediction. The size of the input and hidden of the network has been varied relying on prediction horizon, while the output layer has the single node (Daliakopoulos et al., 2005; Nasir et al., 2011). Each neuron in one layer is linked to the neurons in the next layer, whereas there are no links between the units of the same layer even though the number of neurons in each layer may vary depending on the problem. (Garcia & Shigidi, 2006; Juahir, Zain, Toriman, Mokhtar, & Man, 2004; Nasir et al., 2011). The number of hidden layer nodes is decided by the operator. According to (Kim, Loucks, & Stedinger, 2012), there is no way to decide the best number of hidden nodes without training several networks and calculating the generalization error of each. But, the optimum number of neurons is set as 50%,75% and (2n+1) of input nodes by(Chaipimonplin, 2016).The number of hidden nodes is determined set by the user(Hajnayeb, Ghasemloonia, Khadem, & Moradi, 2011). Another rule of thumb is that the network will never require more than twice the number of hidden nodes as used for input (2n + 1) (Fletcher & Goss, 1993; Singh, Basant, Malik, & Jain, 2009; Swingler, 1996) That's the reason, in this investigation one hidden layer has been selected for modelling and the number of the hidden neuron is set (n+1) and (2n+1) of input nodes to determine the best number of hidden nodes by using two types hidden nodes set.

5. Model performance.

Three types of measures are used in order to judge the performance of each network and its ability to reach specific prediction. To evaluate the model's performance, Coefficient of Efficiency (R^2), Root Mean Square Error (RMSE) and percent residual error (%RE). The best fit between observed and predicted value is high correlation coefficient (R^2) = 1 and low mean squared error (MSE) = 0 (Chaipimonplin, 2016; Daliakopoulos et al., 2005; Nasir et al., 2011; Wechmongkhonkon & Areerachakul, 2012).

Firstly, the function is Efficiency criterion R^2Which is given "(2)"

$$\boldsymbol{R^2 = 1 - \frac{\sum (X_i - Y_I)^2}{\sum X_i^2 - \frac{\sum Y_i^2}{n}}} \qquad \text{"(2)"}$$

Where X_i is observed data, Y_i the predicted data and n is the number of observation explained by the model. The value of (R^2) is near to 1 that means the model performance for prediction water quality index is optimal.

Secondly, function is Root Mean Square Error (RMSE) calculated by "(3)"

$$\boldsymbol{RMSE = \sqrt{\frac{1 \sum_i^n (X_i - Y_i)^2}{n}}} \qquad \text{"(3)"}$$

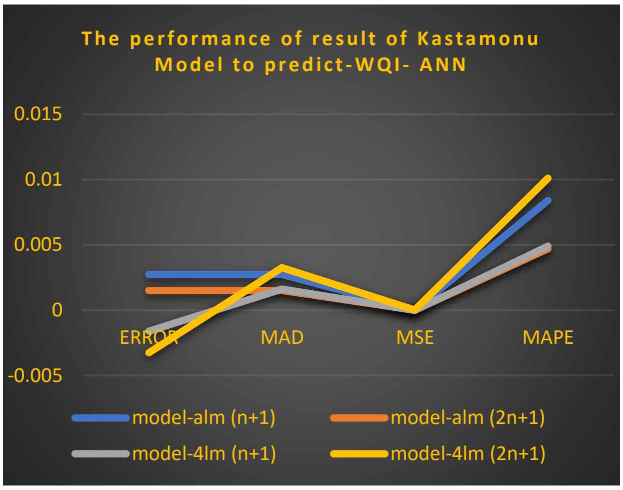
The value of (RMSE) is near to 0 that means the model performance for prediction water quality index is optimal.

The third function is percent residual error (%RE) which calculated by "(4)"

$$\%\boldsymbol{RE = \frac{(X_i - Y_i)}{X_I} * 100} \qquad \text{"(4)"}$$

Table .5. the total performance of ANN-LM models.

Model of Kastamonu city to predict-WQI- model1				
Type of model	**ERROR**	**MAD**	**MSE**	**MAPE**
model-alm (n+1)	0.002729	0.002729	7.45E-06	0.84%
model-alm (2n+1)	0.00152	0.00152	2.31E-06	0.47%
model-4lm (n+1)	-0.00161	0.001605	2.58E-06	0.49%
model-4lm (2n+1)	-0.00326	0.003265	1.07E-05	1.01%

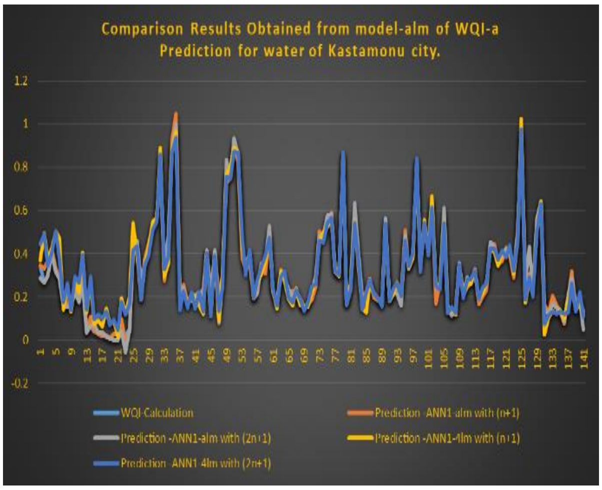


“Fig. 4”. the performance of result of Kastamonu Model predict-WQI- models

Results AND DISCUSSION

Molding Discussion and Results.

The best model utilizing the standard back-propagation algorithm (Levenberg-Marquardt backpropagation) ANN-lm as activation function (model-lm) to prediction water quality index and determined any parameters that give us the best predictions. It is not limited by the number and the nature of the input parameters. R-value, MSE, and MAPE of the model were the deciding criteria to select the optimum models and hidden layers. The comparison of the model-lm for calculated and predicted WQI for water in Kastamonu city are depicted in “Fig.5” it demonstrates the compliance between the calculated and the predicted output by optimal model during workout number. It was structure model-4Lm with (n+1) for WQI gave the best prediction. While model-alm when use whole parameters gave the best prediction with (2n+1) hidden neuron. The results of this research suggested that it is potential to predict the WQI values in the water supply of Kastamonu city by using model-lm with a limited number of input variables when use (n+1) hidden neurons while model-alm using whole variables that requires (2n+1). "Fig.5" shows the comparison Results Obtained from model-alm with (n+1) and(2n+1) of hidden neurons to WQI- Prediction for water of Kastamonu city.



"Fig. 5" Comparison Results Obtained from model-alm and -4lm of WQI-a Prediction for water of Kastamonu city.

CONCLUSION AND RECOMMENDATION.

In this paper, ANN-lm model was improved to predict water quality index (WQI) in municipality water of Kastamonu city. The better prediction accuracy model is model-4Lm with (n+1) for water quality index (WQI) when we used 4 parameters Maybe because there is a strong statistical relationship between a types of variables inputs and WQI outputs. While the model-alm with (2n+1) hidden layer neurons was the better prediction accuracy model when using all parameters, we need increase the hidden node in the model.

1. The model's prediction allows the user to prediction water quality index the water drinking in kastamonu city as well as the change in the number of monitored parameters between two models that used 12 parameters and 4 parameters.
2. The feed-forward network with back propagation learning algorithm was employed
3. As a result, this study shows that the ANN-lm can be employed as useful techniques for the prediction of surface water quality as they change the calculation of the WQI and decrease great efforts and time by improving the computations.
4. These kinds of techniques can be commonly utilized for any aquatic system.
5. This research should encourage the managers and authorities to use the ANN-lm model as more direct and very effective options to predict surface water quality and other water bodies.
6. The number of hidden neurons directly impacts the performance of the network. For that reason, many empirical investigations are carried out by using the deferent set of hidden neurons.
7. If there is the significant relationship between inputs and outputs that they no change in hidden nodes at (n+1) but if we used all variables we need increase the hidden node in the model and change the activation function. it will need to use the hidden node set as (2n+1).

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