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Application of Artificial Neural Networks ANN and Adaptive Neuro Fuzzy Inference System ANFIS Models in Water Quality Simulation of Tigris River at Baghdad City

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ABSTRACT

In this paper two different types of artificial neural networks LMNN, SCGNN applied to simulate the total dissolved solids at of Tigris River at El-Wihda station using different water quality parameters data (pH, Temp., Hardness, Turbidity, EC, SO4, CL) at different stations upstream El-Wihda station. Different architecture and different input combinations with trying different numbers of neurons at the hidden layer. In addition, another application, which is an adaptive neuro fuzzy logic inference system ANFIS applied for the same purpose, the results shows that Even though the available data size is relatively small, reasonably a very good results found and a high performance obtained for the water quality prediction. Both ANN and ANFIS models show a very good performance in simulation of the TDS at the required station, and for the two types of ANNs, It can see that LMNN is better than SCGNN.

Keywords: Water quality, ANN, LMNN, SCGNN, ANFIS.

1 Introduction

Over the past two decades, the use of artificial neural networks has become widely used in environmental modeling, such as forecasting the quality and quantity of water in rivers and lakes. The use of this water for different purposes requires determining their suitability for specific use by matching their characteristics with the standards for each use. The aim of this study is to examine the possibility of using this technique in predicting the quality of the Tigris River during its passage in the city of Baghdad and matching the results with the field measurements based on available data for water quality in several sections along the river. Neuro Fuzzy method was used to classify water quality in China's major rivers. Data from 100 monitoring stations were collected over nine weeks for some physical chemical properties, including chemical oxygen demand, dissolved oxygen, and ammonia. Results showed that 89.59% of data could be properly classified using this method, and it is applicable to water quality assessment [1]. The nine-year data from 1990 to 1998 were used to calculate the concentration of dissolved oxygen based on the daily measurements of pH, discharge, temperature, and materials. In addition, the dissolved oxygen concentration in water quality assessment of reservoirs was determined using radial basis neural network (RBNN) and adaptive neuro-fuzzy inference system (ANFIS). The results showed that the RBNN method

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was better than the ANFIS method in calculating dissolved oxygen concentration[2]. ANN and ANFIS were used to model the dissolved oxygen concentration of the Khoram-Abad River in Iran for 12 months based on river discharge, flow velocity and dissolved oxygen concentration[3]. For calculating the concentration of dissolved oxygen, biochemical and chemical oxygen demand in the Karun River in Iran through the application of MLP, RBNN, and ANFIS. Nine water quality variables were used in the model. The results showed that RBNN and ANFIS were the best in predicting [4].

The ANN method was used to predict the concentration of total Dissolved solids in the Euphrates River in Iraq. The flow of the river, year, month, and the distance of the measurements station from upstream were adopted as inputs for the model used over 14 years. The results showed that the ANN method can be used to predict dissolved solids, and river flow affect the TDS concentration by 75% followed by 61% for the distance of the station, then 33% for the year of measurements, while the month had no more than 4%[5]. In a study carried out by [6] to evaluate water quality of reservoirs using the ANFIS method and RBNN method where the results proved that ANFIS is better than in the prediction of dissolved oxygen concentrations, total phosphorus, and chlorophyll.

2 Methodology

2.1 Concepts of Artificial Neural Networks

The concept of artificial neurons was produced in 1943 [7], and applications of ANNs in many fields started with the introduction of the back-propagation training (BP) algorithm for feed forward ANNs in 1986 [8]. An artificial Neural networks ANN are computing systems. Each system is composed from highly interconnected neurons which are simple information processing nodes or units .These neurons are gathering the information's (inputs) from both single and multiple sources then provides output which is related with the inputs by nonlinear relation. ANNs explain non-linear relations with different factors that are adjusted (calibrated or trained) in such a way that the ANN's output approximates the observed output on a data set. ANNs need quite enough amount of historical data to be trained upon satisfactory training, an ANN should be able to provide output for previously ''hidden" inputs. The main differences between the various types of ANNs involve network architecture and the method for determining the weights and functions for inputs and neurons this is what could be described as training operation [9].

2.1.1 Levenberg-Marquardt Method for Neural Networks Training

Many researches have been produced many methods to ensure the effeciency of backpropagation BP algorithm. All of these methods lead to low acceptable results. The Levenberg-Marquardt (LM) algorithm [10] ensued from development of BP (Back propogation) algorithm dependent methods. This method gives a good exchange between the speed of the Newton algorithm and the stability of the steepest descent method [11], that those are two basic theorems of LM algorithm. It is impossible to reduce error oscillation. Other effort with variable decay rate has been ensued to reduce error oscillation [10], but offered algorithm had low speed compared standard LM algorithm. LM can be described as a combination of steepest descent and the Gauss-Newton method. When the solution becomes far from the correct one, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Gauss-Newton method [12].

2.1.2 Scaled Conjugate Gradient Type Method With Convergence For Back Propagation Neural Network

Scaled Conjugate Gradient Method SCG is a supervised learning algorithm for feed forward neural networks. This method is used to reduce the error value between the result of the network and the real output or the observed one. It can be represented by following equation that indicates the quadratic approximation to the error E in a neighborhood of a point w by:

$$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E^{"}(w) y \tag{1}$$

The critical points for Eqw(y) must be found for calculating the minimum Eqw(y). The critical points are the solution to the linear system defined by Moller, [13] as:

$$E_{qw}(y) = E^{"}(w) y + E'(w) y \tag{2}$$

The step size scaling mechanism, which is used in SCG, could reduce time consuming line search per learning iteration. This can increase the efficiency and performance [14].

2.2 Concepts of ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

At 1993, Jang proposed multi-layered neural network. The connections in these layers are not weighted or all weights equal to one [15]. ANFIS can be considered as an alternative manner that consists the advantages of two intelligent approaches neural network and fuzzy logic to ensure rational reasoning in quantity and quality. This new network has a high ability of training by means of neural networks and linguistic interpretation of variables via fuzzy logic. ANFIS implement a first order Sugeno style fuzzy system; it applies the rule of TSK Takagi Sugeno and Kang form in its architecture [16].

2.2.1 Traning of ANFIS (Learning Algorithm)

The membership function parameters of each input, the consequents parameters also number of rules are the most important parameters which should be tuned in an ANFIS model .The training process should consists two important steps which are Structure learning that ensures determining approopriate structure of the network that is, the best partitioning of number of membership functions for each input and number of rules. The second step is parametric learning whch suggest the membership functions and consequents parameters. The most common training algorithm is the hybrid learning. This algorithm is carried out in two steps: forward pass and backward pass, once all the parameters are initialized, in forward pass, functional signals go forward till fourth layer and the consequents parameters are identified by least square errors. After identifying consequents parameters, the functional signals keep going forward until the error measure is calculated. In the backward pass, the error rates propagate backward and the premise parameters are updated by gradient decent.

3 Case study and Nature of data

Tigris River is one of the two main rivers in Iraq. Its length is about 1850 km, while its length at Iraq is about 1418 km. This River is rising in the Taunus Mountains of Eastern Turkey. The river flows for about 400 km through Turkey before entering Iraq. It drains an area of 473 103 km^2.This area is shared with two other countries Turkey and Syria. About 58% of the basin lies in Iraq, and no major tributary joins the Tigris south of Baghdad [17, 18]. There are more than eight water treatment stations on Tigris River. The well registered data are at stations El-karkh, Eastern of Tigris, El- wethba, El-kerame, El-qadisiye, El-dora, El-rasheed, El-wihda .These stations are at Baghdad city as they are shown in Figure (1). Different water quality parameters measurements are available at the stations .These data are observed as monthly data from 2009-2013. In this paper the observed values of water quality parameters which are selected after a brief correlation test to be Temperature , hardness, PH , Turbidity , Electrical conductivity , SO_4, Cl and total dissolved solids TDS at 9 stations were used in simulation operation . Seven of these stations were considered as upstream stations which are El-karkh, Eastern of Tigris, El- wethba ,El-kerame , El-qadisiye, El-dora, El-rasheed and the last station which is El-wihda st was considered as downstream station.

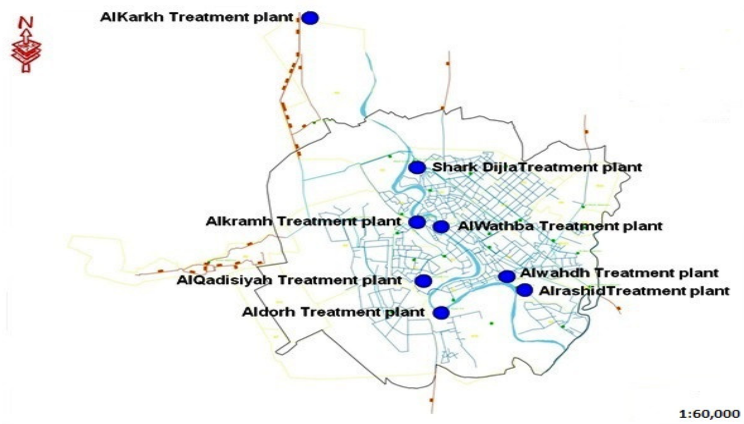

Figure (1) Study Area

3.1 Data Pre-processing

To ensure that all variables receive equal attention during the training process, they should be standardized. There many equations which provide a standardized data. For example, as the outputs of the logistic transfer function are between 0 and 1, the data can be scaled in the range 0.1–0.9 or 0.1–0.8. Before using the data for ANN, the data has been pre-processed (normalized). The same is true for adaptive neuro fuzzy system ANFIS since both models work best if the inputs are scaled to the same range of values [19]. In this study the best equation to standardized the data was found to be

$$Xi = 0.1 + 0.8\frac{(X - Xmin)}{(Xmax - Xmin)} \tag{3}$$

Xmin, Xmax are the minimum and the maximum values of the observed data series.

4 Results and discussion

Two types of artificial neural networks were tried in this study, which are LMNN, SCGNN to simulate the different parameters of water quality of Tigris River. Matlab (2014a, 8.3.0.532) neural network toolbox was used for the implementation of neural networks models. In both applied kinds of ANN, the data set was divided into two sets training and test. The training set was selected to be %60 from the whole data while the test set was chosen as %40 from the data. Different architectures were tried as different input combinations, which mean different water quality parameters at different sites. The output in all tried models is selected to be Total dissolved solids at downstream of Tigris river which is at the station of Al-wihda. The number of hidden layer was selected to be one hidden layer with different number of neurons. Following Table (1) shows the different applied models of ANN for both types LMNN and SCGNN.

Table 1 Description of the applied ANN models.

Model Name	Inputs	Output
MI	(Tem,Har,pH,Turbidity,EC,SO4,CL,TDS) at 7 upstream stations &(Tem,Har,pH,Turbidity,EC,SO4,CL) at d/s station	TDS at Al-Wihda station
MII	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at Al-Wihda station
MIII	(TDS)at all 7 u/s stations	TDS at Al-Wihda station

Tem: Temperature, Har: Hardness, EC: Electrical Conductivity, CL: chloride, TDS: Total dissolved solids.

4.1 Performance Parameters

Four statistical performance parameters, which are the determination coefficient (R^2), Nash-Sutcliffe efficiency (E_{Nash}), percent bias (R_{Bias}) and mean absolute percent error (MAPE), were used to assess the models' performances. These parameters are defined as:

$$R^2 = \frac{\left(\sum_{t=1}^{n}(A_t - A_{mean})(S_t - S_{mean})\right)^2}{\sum_{t=1}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(S_t - S_{mean})^2} \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{A_t - S_t}{A_t} \right|. \tag{5}$$

$$ENash = 1 - \frac{\sum_{t=1}^{n}(A_t - S_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2} \tag{6}$$

$$R\ bias\ = 100 * \frac{\sum_{t=1}^{n}(S_t - A_t)}{\sum_{t=1}^{n} A_t} \tag{7}$$

where A_t is the actual value and S_t is the Simulated value. S_{mean}, A_{mean} are the mean value of the series [20, 21]. The best value of R^2 is 1.0 while, the optimum value of R_{Bias} is 0.0 and a better description of R_{Bias} and E_{Nash} was given also by [22, 23], this description can be summarized as:

$Very\ Good(VG)$	$0.75 < E_{nash} \leq 1$	$R_{bias} < \pm 10$
$Good(G)$	$0.65 < E_{nash} \leq 0.75$	$\pm 10 \leq R_{bias} \leq \pm 15$
$Satisfactory(S)$	$0.5 < E_{nash} \leq 0.65$	$\pm 15 \leq R_{bias} \leq \pm 25$
UN$Satisfactory(US)$	$E_{nash} \leq 0.5$	$R_{bias} \geq \pm 25$

4.2 ANN application Results

For ANN development, a number of input combinations and input stations were tried, as it is clear from the above Table .This means that the input nodes for the three above models were 71 nodes, 7 nodes, 8 nodes respectively. The output layer had a single node which is the required TDS at d/s station Al-Wihda. During the training process the number of hidden layer nodes was tried to be less than (2* input layer nodes +1) [24]. The comparative performance of different ANN models based on E_{nash}, Coefficient of correlation R^2, R_{bias}, MAPE were calculated, and the selection of the best performance was depended on the best results of these parameters. Table (2) shows the results of performance parameters for the different ANN applied models. The Table concentrates on the best performance among all the applied models since different e number of neurons at the hidden layer were applied until reaching the best result.

Table 2 results of the performance parameters of different ANN applied models for Training Period

Model Name	Type of ANN	Inputs	Output	Best Architectur	E_{nash}	R^2	R_{bias}	MAPE
MI	LMNN	(Tem,Har,PH,Turbidity,EC,SO4,Cl,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,Cl) at d/s station	TDS at d/s station	63-22-1	0.87	0.88	-13.3	28.85
MII	LMNN	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	7-10-1	0.98	0.987	+9.1	22.53
MIII	LMNN	(TDS)at all 8 u/s stations	TDS at Al-Wihda station	7-14-1	0.93	0.941	-8.8	24.60
MI	SCGNN	(Tem,Har,PH,Turbidity,EC,SO4,CL,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,CL) at d/s station	TDS at d/s station	63-9-1	0.734	0.734	+16	33.62
MII	SCGNN	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	7-7-1	0.75	0.734	-17	38.85
MIII	SCGNN	(TDS)at all 8 u/s stations	TDS at d/s station	7-9-1	0.73	0.73	+16	38.24

Table (3) produces the results of the same process for test period, which is more important in deciding the success of any mathematical model. According to the above results, it is clear that the best result was found using Levenberg-Marquardt Method, since the performance is clearly reduced by using the Scaled conjugated gradient method in training the ANNs. The best input combinations was found to be for model MII with seven input nodes (Temperature ,Hardness, PH, Turbidity, Electrical conductivity , SO4, CL) at downstream station which is El-Wihda station. This was true for both kinds of the artificial neural networks. Table (3) also shows the best number of neurons at the hidden layer for all applied kinds and different input combinations.

Table 3 results of the performance parameters of different ANN applied models for Test Period

Model Name	Type of ANN	Inputs	Output	Best Architecture	E_{nash}	R^2	R_{bias}	MAPE
MI	LMNN	(Tem,Har,PH,Turbidity,EC,SO4,CL,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,CL) at d/s station	TDS at d/s station	63-22-1	0.863	0.861	-12.13	28.77
MII	LMNN	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	7-10-1	0.99	0.999	+7.1	22.67
MIII	LMNN	(TDS)at all 8 u/s stations	TDS at Al-Wihda station	7-14-1	0.993	0.993	-7.8	25.98
MI	SCGNN	(Tem,Har,PH,Turbidity,EC,SO4,CL,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,CL) at d/s station	TDS at d/s station	63-9-1	0.74	0.744	+17.1	34.61
MII	SCGNN	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	7-7-1	0.76	0.75	-17	38.86
MIII	SCGNN	(TDS)at all 8 u/s stations	TDS at d/s station	7-9-1	0.71	0.71	+15.3	39.21

The best number of neurons at the hidden layer for MII-LMNN type was found to be 10 neurons while for MII-SCGNN was 7 neurons. Values of R_{bias} or first successful model, which is MII–LMNN indicates to an overestimating while the best SCGNN model the R_{bias} value indicates to an underestimating. It is important to mention that all the tested architectures (different input combinations) for LMNN showed better performance if compared with SCGNN networks. Figure (2) represents the best ANN architecture that showed the best performance.

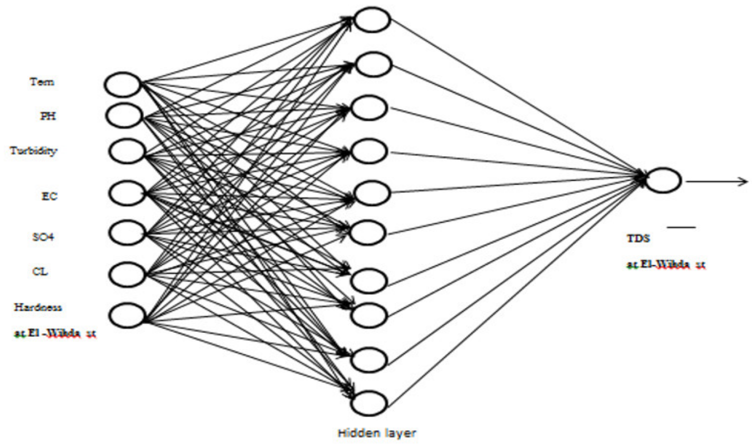

Figure 2 MII-LMNN architecture.

Figure (3) shows the comparison of the best three models with the observed data. The Figure represents the simulated TDS at A-Wihda station for test period by the successive models with the actual data, which means the observed values.

4.3 ANFIS application Results

To apply the adaptive neuro fuzzy interference system ANFIS models, the same architectures were used after applying the same manner in the standardization of data. Fuzzy system is based on the logical rules of premises and conclusions, which cannot be analyzed with the classical probability theories. On the other hand, artificial neural networks are capable of creating relevant relations between input and output variables through their learning capabilities based on various training patterns. A combined system of fuzzy inference and artificial neural network capable of using numerical data for predicting outputs can create a powerful tool that has come to be called the adaptive neural-fuzzy inference system. In this combined system, the fuzzy part establishes relations between input and output variables while the fuzzy membership functions are determined by its neural network part. By using the same input combinations and same training and test periods and by using 112 runs of the adaptive neuro fuzzy inference system with network segregation method, different results were found. This was done through using Matlab (2014a ,8.3.0.532) for network segregation . Tables (4),(5) show the results of application of ANFIS model on the selected of input combinations for the same training and test periods respectively. It is important to mention that the method of segregation was preferred on the partial clustering method due to the choice of type and number of membership functions, which can be determined by the user.

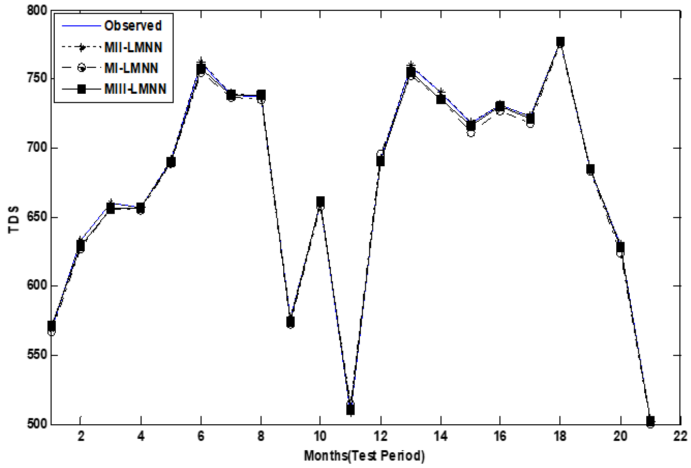

Figure 3 Comparison between the best three ANN models with the Observed data

Table 4 produces the results of the same process for test period

Model Name	Inputs	Output	Description	E_{nash}	R^2	R_{bias}	MAPE
MI	(Tem,Har,PH,Turbidity,EC,SO4,CL,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,CL) at d/s station	TDS at d/s station	Segregation	0.739	0.729	-15.1	32.71
MII	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	Segregation	0.961	0.962	**+7.3**	24.007
MIII	(TDS)at all 8 u/s stations	TDS at Al-Wihda station	Segregation	0.851	0.85	-7.9	27.98

Table (5) results of the performance parameters of different ANFIS applied model for Training Period.

The approximate results to the previous ANN results were found since the same input combinations were found to be most successful combinations according to the same evaluation parameters. Figure (4) shows the comparison between the observed values and the simulated values by the best ANFIS model.

It can be seen that al the three models of ANFIS show a good performance in simulating of TDS values This indicates the capability of ANFIS models in making predictions on the basis of input data sets . The second model which inputs are Temperature, Hardness, PH, Turbidity, Electrical conductivity, SO4, CL at the downstream station exhibits a better performance compared to the other two . Comparison of the results obtained from the nine different models (six models ANN and three of ANFIS) revealed that increasing the number of input parameters dose not necessarily enhance model performance or increase the accuracy.

Table 5 results of the performance parameters of different ANFIS model for Test Period

Model Name	Inputs	Output	Description	E_{nash}	R^2	R_{bias}	MAPE
MI	(Tem,Har,PH,Turbidity,EC,SO4,CL,TDS) at 8 upstream stations &(Tem,Har,PH,Turbidity,EC,SO4,CL) at d/s station	TDS at d/s station	Segregation	0.729	0.729	-15.99	34
MII	(Tem,Har,PH,Turbidity,EC,SO4,CL) at Al-Wihda station	TDS at d/s station	Segregation	0.95	0.968	+8.3	**26**
MIII	(TDS)at all 8 u/s stations	TDS at Al-Wihda station	Segregation	0 843	0.849	-9.9	29.6

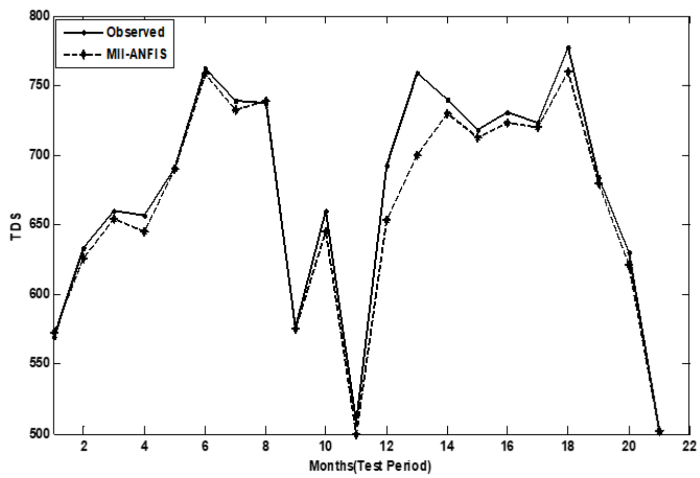

Figure 4 comparison between the best ANFIS (MII-ANFIS) model and the observed data

5 Conclusions

Followings are the most important conclusions, which found;

1. Even though the available data size is relatively small, reasonably a very good results found and a high performance obtained for the water quality prediction. If more data become available, better estimation can be using the successful models.
2. Both ANN and ANFIS models show a very good performance in simulation of the TDS at the required station
3. By comparing the two types of ANNs, It can see that LMNN is better than SCGNN.
4. Increasing the number of input parameters does not necessarily enhance model performance or increase the accuracy; this is true for both ANN models and ANFIS models.

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