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Modeling Lake Urmia Water-level Changes using Local Linear Neuro-Fuzzy Method

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ABSTRACT

According to the water resources and climate change and challenges of Urmia Lake basin, which is the discharge and final destination of North West rivers, a model was presented. Due to climate change and water resources in river basin such as rainfall, climate change in basin that has direct impact on evaporation over water catchment areas and lake water, this model can be provided. In addition, the inflow to the lake and the lake water-level fluctuations with the high accuracy and acceptable to experts could be estimated by this modeling and the lake water-level is going to be predicted up to one month. In order to simulate monthly fluctuations of the Lake water-level, this paper dealt with modeling the lake water level using two methods, Water Balance Equation and Local Linear Neuro-Fuzzy Network. In this study, to evaluate models' accuracy, all of them were assessed by three most famous criteria including Root Mean Squares Error (RMSE), correlation coefficient (R), and similarity. The results obtained by Local Linear Neuro-Fuzzy Network modeling indicated that the concomitant use of cumulative flow (entering the lake), monthly precipitation and monthly evaporation on the lake surface provided the best performance with high accuracy regarding the simulated fluctuations of the monthly water level in Urmia Lake.

Keywords

Balance Equation, Urmia Lake, Nuero-Fuzzy Modeling, Simulation

1. Introduction

Descending trend of the Lake Urmia's water level as one of the most significant lakes of Iran and the second largest salt water lake on the earth goes to the extent that in addition to conservationist groups and water resource experts, it has also attracted the attention of others interested in this unique ecosystem. Wetlands can be considered as greatest biologically diverse of all ecosystems, serving as home to a wide variety of plant and animal life. In addition, wetlands play various roles in the environment, principally water sanitization, flood control, and shoreline stability.

The shrinking of the Urmia Lake has been started from long time ago; in 1996 the lake water surface elevation was reported as 1276.7 m and ever since it has had a decreasing trend. Unfortunately, it has approximately shrunk by 60 % and has converted a national concern. Various opinions have been expressed about any possible factors and their influence on this dropping trend. Certainly demographic development, anthropogenic, agricultural

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development, water resources management and dams, natural and climatic factors all affect the current situation and exacerbate this trend. Delavar et al. (2008) focused their research on the monthly modeling of the water level fluctuations in the Urmia Lake. The results obtained by the MLP neural network indicated better performance in terms of accuracy and sensitivity to the input parameters than water balance and multiple correlation equation.

Mohammadi et al. (2011) used three methods of water balance equation, multiple correlation equation and MLP neural network to model water level of the Urmia Lake in a similar research. The results of this study also indicated that if properly trained, the neural network can estimate the Lake water level. Talebizadeh and Moridnejad (2011) developed ANN and ANFIS models to predict the Urmia Lake water level changes in an engrossing research and found that the results of ANFIS model were superior to ANN. Furthermore, in another work conducted on the Urmia Lake, Kavehkar et al. (2011) examined the prediction performance of GP compared to ANN and noted that the GP performed marginally better for most of the cases. Karimi et al. (2012) used two intelligent methods of ANFIS and GEP for predicting water-level fluctuations of the Urmia Lakea and indicated that GEP surpassed the ANFIS model (Neuro-Fuzzy Inference System). Exploiting ANFIS and ANN models for predicting sea level in Darwin Harbor Australia was the subject of another research by Karimi et al. (2013). The outcomes expressed the same performance for both mentioned models. Hassanzadeh et al. (2012) investigated main factors that reduce the Lake Urmia water level. They determined biggest contributors to the descending trend as changes in inflows, constructing dams, and less precipitation, which are 65%, 25% and 10% responsible for the problem, respectively.

Modeling (including simulator and predictor models) of the water level fluctuations of the Lake Urmia, which is an endangered ecosystem and a nonlinear complex natural phenomenon, can help in attenuating damages caused by the natural hazards such as drought and flood (Roshan, 2013, Tabari, 2013).

Nouri et al. (2014) modeled the lake water surface by using Support Vector Machine techniques (SVM) and a combined model of Wavelet and neural network and reported that SVM model performed better than the other combined models. Kakahaji et al. (2013) predicted fluctuations of the Lake Urmia using linear static models (ARX and BJ) and intelligent models (LLNF and MLP) and concluded that results of LLNF outweigh other investigated methods.

In this paper, monthly rate of all the hydrometric stations was used and it was attempted to normalize flow. Eventually, monthly discharge with subtracting uses at the upstream station was utilized. In addition, by using the balance method, accurate Pan coefficient was estimated. In order to obtain the evaporation at the lake surface and simulate the lake water level fluctuations, water balance equation and Local linear Neuro-Fuzzy networks were used.

2. Materials and Methods

2.1 Water Balance Equation: a common traditional method

Balance method is a traditional method for volume flow rate estimation. In this method, the effective components of water volume based on their linear effect are considered in the water balance equation and monthly water volume is determined. Balance equation of the Urmia Lake is shown as below:

$$\Delta H(k) = P(k) - E(k) + 0.001(\frac{R_{in}(k)}{A(H)})$$
$$\hat{H}(k) = \hat{H}(k-1) + \Delta H(k) \quad (1)$$

where P is Precipitation on the lake surface (mm), E is Evaporation on the lake surface (mm), R_{in} is the volume of incoming flow (m^3), A is lake area (km^2), and k indicates a particular month. In addition, H^(k) and *ΔH(k)* represent lake lave and level changes in the *k*th month.

2.2. Multi-layer Perceptron Network

All previous mentioned methods can be specified as linear tools. For prediction purpose, the inputs/output recorded data are available, previous inputs and outputs are injected into the static model. Thus, the input vector can be defined as follows:

$$\underline{X} = \left[U_1(k), U_2(k), \ldots, U_p(k), y(k-1), y(k-2), \ldots, y(k-n)\right]^T \quad (2)$$

where *y(k−n)* is *n*th past value of real output and *Up(k)* contains past values of the *p*th input process according to:

$$U_p(k) = \left[u_p(k), u_p(k-1), u_p(k-2), u_p(k-3), \ldots, u_p(k-m_i)\right] \quad (3)$$

where m_i denotes the order of *p*th input, and *n* is the output order.

Note that in the current study, process refers to the Lake Urmia. In practice, any nonlinear static approximator can be used instead of intra nonlinear model. Indeed, Fig. 1 consists of two parts: a nonlinear static approximation and external dynamics. Thus, the resulted model is able to approximate nonlinear dynamic systems.

Although static MLP networks can be utilized for modeling static systems as well as the systems with low grade of dynamism, it is better to use them in a dynamic form to identify model of process with high grade of dynamism. A static multi-layer perceptron can be used instead of nonlinear static model, despite other probable alternative are also possible (e.g., LLNF model). It can be seen that none of the past recorded inputs and outputs values are applied into the network (Nozari et al., 2012).

Since it has been proven that MLP network with one hidden layer has a better performance in prediction purposes (Nelles, 2001, Cybenko, 1989, Hornik et al., 1989), in the present study, the MLP model architecture has one-hidden-layer which is depicted in Fig. 2. Moreover, it must be noted that since recorded data are positive, the activation functions of hidden neurons decided to be logistic function.

In training process, in order to minimize error, neural networks try to update their parameters based on learning algorithm and consequently produce proper output associated with the given input. There are many learning algorithms such as Gauss-Newton (GN), Gradient Descent (GD), and Levenberg-Marquardt (LM) (Hagan & Menhaj, 1994). It was decided to use the LM algorithm to update the MLP network parameters due to the following advantages: (1) faster convergence compared with the GD method, (2) more robustness compared with the GN method, (3) an interpolation between the GN and GD methods (i. e. it has the speed of GN and the convergence of GD) (Haykin, 1999). The LM algorithm updates the parameters of the MLP neural network according to Eq. (8).

$$\begin{cases} W_{n+1} = W_n + \Delta W \\ \Delta W = -\left(\left[J^T(W)J(W) + \mu I\right]^{-1}\right)\left(J^T(W)e\right) \end{cases} \quad (4)$$

where e is the error function, J is a Jacobian matrix, and μ is a scalar that makes LM closed to either GD or GN. Here, W contains the weights of the network and is defined as follows:

$$W = \left[w_{110} w_{111} \ldots w_{11D} w_{1L0} w_{1L1} \ldots w_{1LD} w_{210} w_{211} \ldots w_{21L}\right] \quad (5)$$

2.3. Neuro-fuzzy networks

Different methods for system identification by using fuzzy systems have been proposed such as Takagi-Sugeno, Adaptive Neuro–Fuzzy Inference System (ANFIS) and Locally Linear Model (LLM). In this study, the Locally Linear Model was used which models and identifies nonlinear systems by the Fuzzy rules, and divides the system into incremental smaller linear models. First, locally linear mode was proposed by Oliver Nelles. In this method, Complex systems are divided into a number of locally smaller subsystems with less complexity and each subsystem is presented a linear model. This method is well-known for dividing complex systems into smaller parts. The network structure of Locally Linear Model is shown in Fig. 1. In order to train the parameters in this model, the learning algorithm of Locally Linear Model Tree (LOMILOT) was used.

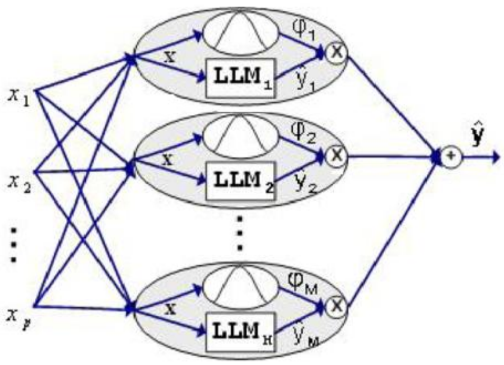

Fig. 1. Neuro Fuzzy Networks (LLM)

Training algorithm of Locally Linear Model Tree can be explained as two inner and outer rings, the outer ring of the system adjusts the position of neurons and the inner ring adjusts its parameters. First, by using a linear model (a neuron) and training data method, weights and parameters of the Gaussian function can be obtained. Each neuron, considering the maximum error of the estimated model, is divided into two other neurons to minimize error. Breaking the neurons cause larger error than the original system and setting the new neuronal parameters will continue until the error is less than entire set limit (The algorithm will be continued to increase the number of its neurons to reach the stopping criteria). The algorithm for 2D of 4-iterated function is shown in Fig. 2.

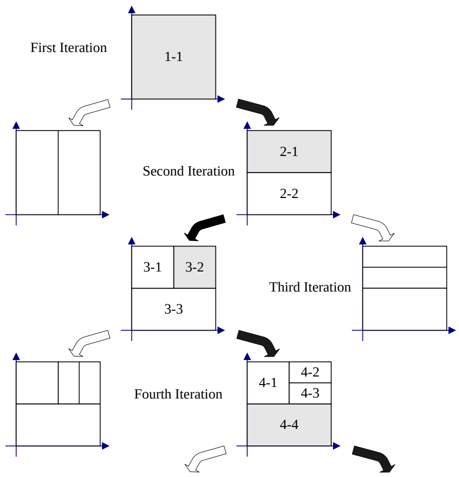

Fig. 2. Divided LOLIMOT algorithm 2D 4-iterated function

Procedure of this method is expressed as the following steps:

To start with the initial model, consider the number of neurons is one ($M = 1$). Due to $\Phi_1(\underline{u}) = 1$ so the system is modeled by a simple linear system.

Worst locally linear model: The model which has the worst locally cost function is chosen for analyzing. (In case m = 1 is the only available model chosen to break). The locally cost function can be considered as below:

$$I_i = \sum_{j=1}^{N} \Phi_i\left(\underline{u}(j)\right)\left(y(j) - \hat{y}(j)\right)^2 = \sum_{j=1}^{N} \Phi_i\left(\underline{u}(j)\right)e^2(j). \tag{6}$$

The largest error in local linear model will be separated by l index.

Investigation of all divided cases (analysis): all divided states in the horizontal and vertical axes will be obtained of l model (the range of perpendicular axis will be divided in half). The number of these states depends on inputs (P mode).

Choose the best mode analysis and network changes: For these P modes, choose the mode that has the low-cost function, then the cells are divided ($M \rightarrow M+1$).

Continue until convergence: Do steps 2 to 4 until the desired error based on the cost function is achieved.

3. Criteria for model Assessment

In this research, for final evaluation of models, three standards were used including Variance (R2), Root Mean Square Error (RMSE) and Similarity. They are all based on the differences between error of actual output and simulated output as follows:

$$\text{RMSE} = \left(\frac{1}{Q} \sum_{j=1}^{Q} \left(H(j) - \hat{H}(j) \right)^2 \right)^{1/2} \tag{7}$$

$$\text{Similarity} = 100 * \left| 1 - \frac{\left\| \hat{H} - H \right\|_2}{\left\| H - \bar{m}(H) \right\|_2} \right| \tag{8}$$

$$\text{Correlation Coefficient} = \frac{\sum_{j=1}^{Q} \left(H(j) - \bar{m}(H) \right) \left(\hat{H}(j) - \bar{m}(\hat{H}) \right)}{\left(\sum_{j=1}^{Q} \left(H(j) - \bar{m}(H) \right) \sum_{j=1}^{Q} \left(\hat{H}(j) - \bar{m}(\hat{H}) \right) \right)^{1/2}} \tag{9}$$

where Q is Number of data, H is observed water level, $\hat{H}$ is estimated water level and m is average function.

4. Case Study

4.1. Urmia Lake Specifications (Description of Study Area)

Lake Urmia is a salt lake in north-western Iran. The lake is between the provinces of East and West Azerbaijan in Iran. It is the largest lake in the Middle East and the sixth largest saltwater lake on earth with a surface area of approximately 5,200 km². This lake is the most important and valuable aquatic ecosystems. In 1975, it was announced as a Ramsar site and an international wetland and in 1977, Urmia Lake declared as a part of protected area of biosphere reserve by UNESCO. Average water level of the Urmia Lake is about 5 to 6 m, which is different in various seasons and years. In June, the water level of lake is about 1 m higher than November. Length of Urmia Lake varies from 130 to 146 kilometers. Widest part of the lake is located on the south side of the lake and is around 58 km wide and narrowest point of the Lake is 15 km. In watershed basin of the Urmia Lake, there are 17 permanent and 12 seasonal river flows. The location of Urmia Lake is shown in Fig. 3.

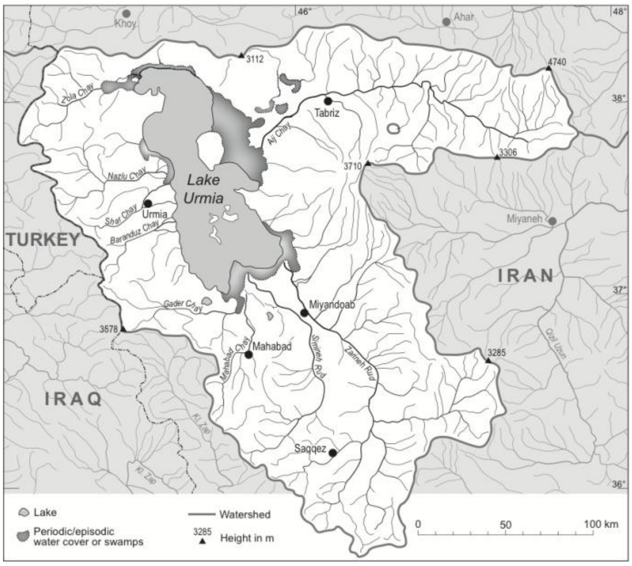

Fig. 3. Location of the Urmia Lake and its watershed basin

4.2 Data and Statistics

Required precipitation and evaporation monthly statistics for the index period (statistics years) (1966-2006) were obtained from Iranian Ministry of Energy. Due to proximity of Sharafkhaneh Station to the Urmia Lake, the precipitation and evaporation data from these stations have been utilized, which represent rainfall and evaporation on the lake surface. All information related to a monthly precipitation and evaporation was used in a linear equation of balance method and nonlinear Neuro-Fuzzy networks.

In order to calculate the actual evaporation at the lake surface ratio of 0.92 in Class A evaporation pan was used. This Ratio (R=0.92) have been obtained by trial and error method and used to maximize the adoption of the calculated water level in balance equation and observed water level.

In this modeling, the monthly flow of these rivers in a period of 40 years from 1966-1967 to 2005-2006 was used. All of them at the entrance of Urmia Lake are equipped by hydrometric stations and their daily flow is measured.

In this method, the input data include entrance flow to the Lake, Precipitation, Monthly evaporation at the Lake Surface and Lake water level is as output.

Monthly statistics observed water level for statistical years of cycle indicators (1966-2006) are available in Iranian Ministry of Energy as shown in Fig. 5.

5. Results and Discussion

Comparison of the obtained results of water balance equation and observed water level is shown in Fig. 5. In addition, the results of the correlation between estimated and observed data obtained from balance equation are shown in Fig. 6.

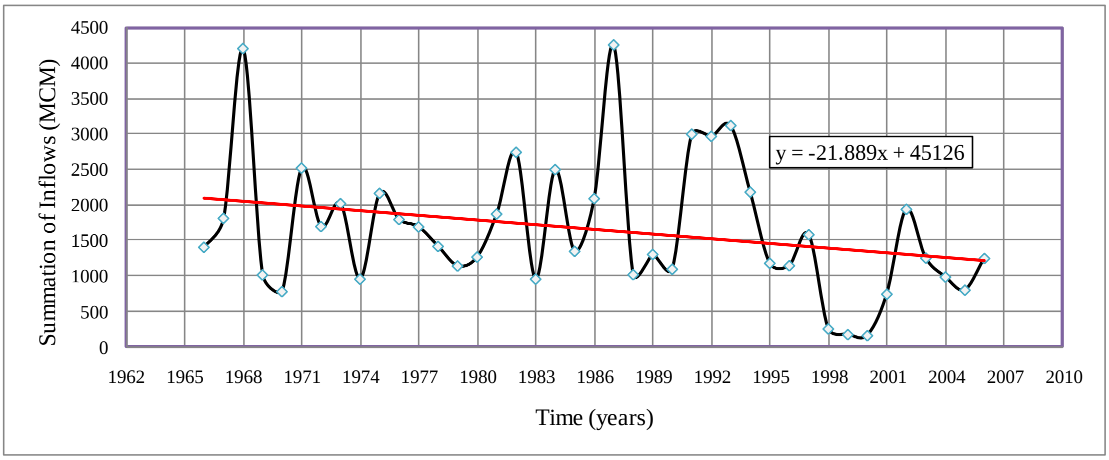

Fig. 4. Entrance flow rate to the lake during the period 1966-1967 to 2005-2006

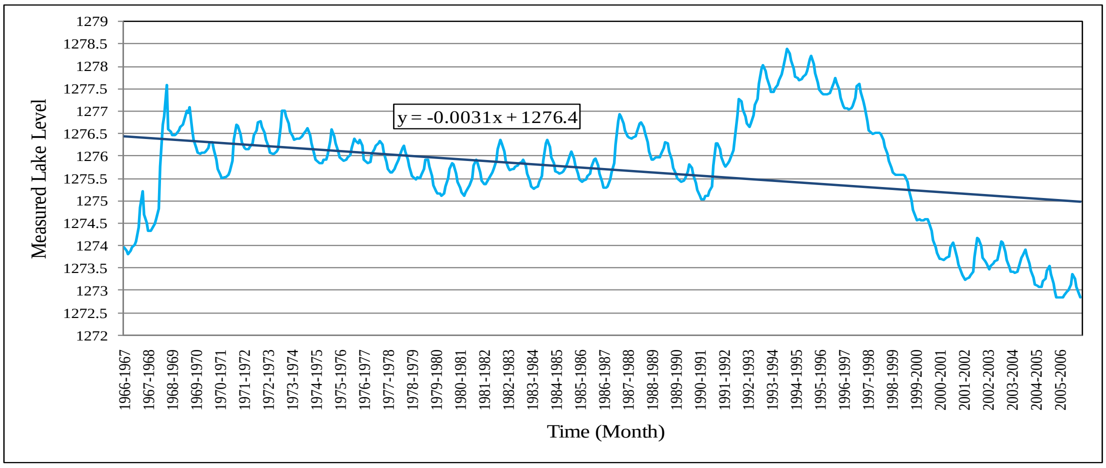

Fig. 5. Lake Urmia water level during the period 1966-1967 to 2005-2006

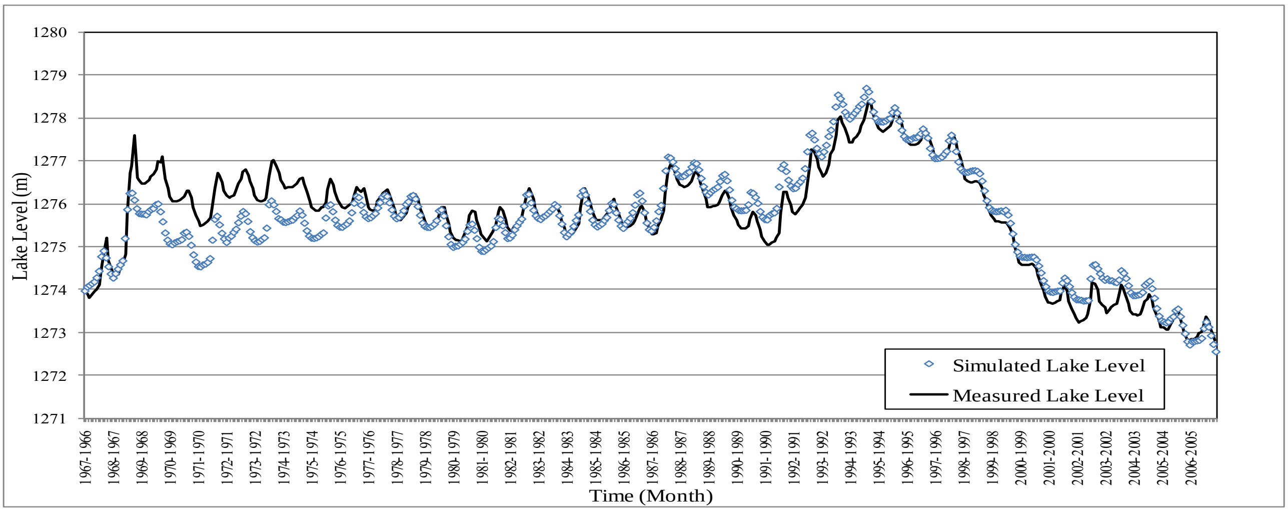

Fig. 6. Comparison of the lake water balance equation results and the observed data

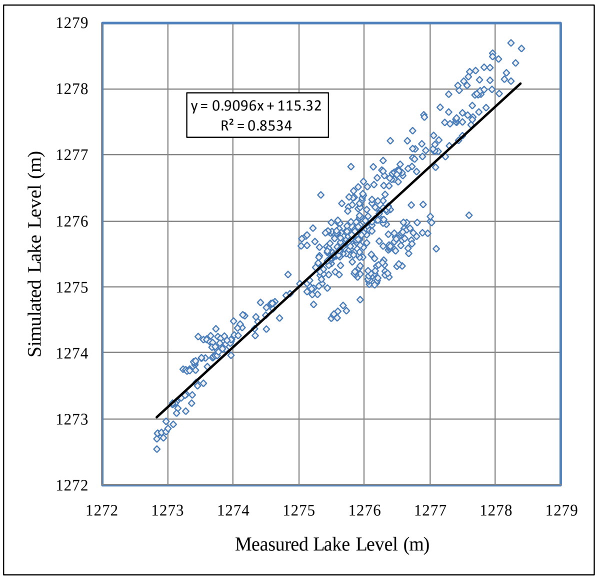

Fig. 7. The results of the Urmia Lake water balance equation versus the observed data

Figure 6 illustrates the balance model in the mid-term period of studies (1986-1987) in which it shows a good performance. However, at the beginning and end of the period, the error rate increased considerably. Since accurate information of the relationship between groundwater and the Lake is not available, it was not possible to enter and improve the balance equation. Moreover, in some cases, the effective information on the Lake water level may be available. However, measuring may lead to excessive complexity of the balance equation and therefore, consciously excluded from the equation. In mathematical models (such as balance and other similar models) these uncertainties lead to inaccurate results. In contrast, in experimental models, the modeling is based on collected data (testing) and easily to accept the changing.

In addition, a multilayer perception (MLP) was proposed and the results were compared with those obtained by the balance and Neuro-Fuzzy Methods. For assessment, the effect of neuron numbers in proposed MLP model, 7, 12 and 14 neurons were considered and results were presented in Table 1. As shown in this table, increase in neuron number caused a better prediction of water level.

Table 1. Structure of all the nonlinear models

Model	Neuron* /Rule** Number	Input structure	Input number
MLP-1*	7	H(k)= f (P(k-1), P(k-2), E(k-1), E(k-2), Rin(k-1), Rin(k-2), H(k-1))	7
MLP-2*	12	H(k)= f (P(k-1), E(k-1), Rin(k-1), H(k-1))	4
MLP-3*	14	H(k)= f (P(k-1), E(k-1), Rin(k-1), H(k-12))	4
DFM-1**	5	H(k)= f (P(k-1), P(k-2), E(k-1), E(k-2), Rin(k-1), Rin(k-2), H(k-1))	7
DFM-2**	8	H(k)= f (P(k-1),..., P(k-6), E(k-1),...,E(k-6),Rin(k-1),...,Rin(k-6),H(k-1))	19
DFM-3**	11	H(k)= f (P(k-1),..., P(k-11), E(k-1),..., E(k-11), Rin(k-1),..., Rin(k-11), H(k-1))	34

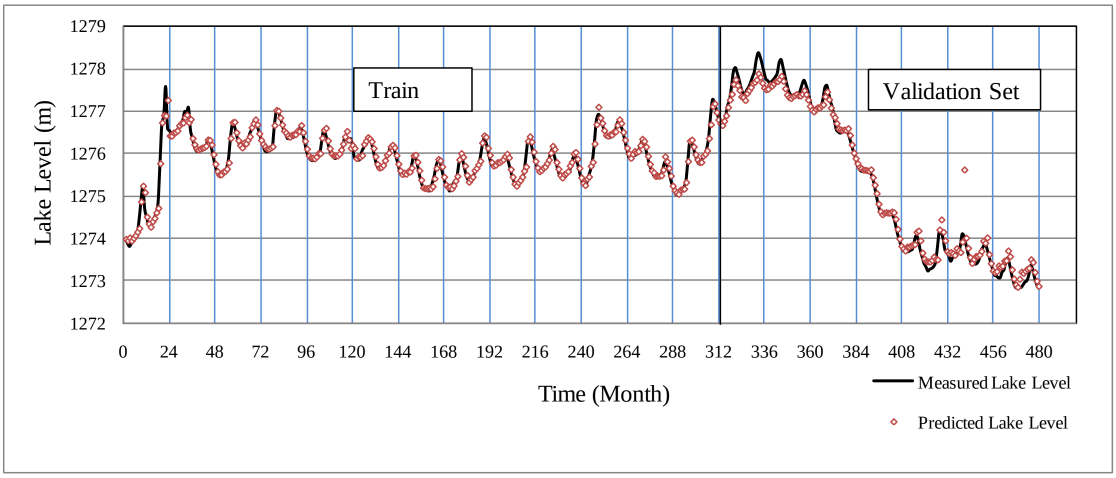

Fig. 8. Comparison of the obtained results using MLP-1 Model (7 Neuron) and observed data

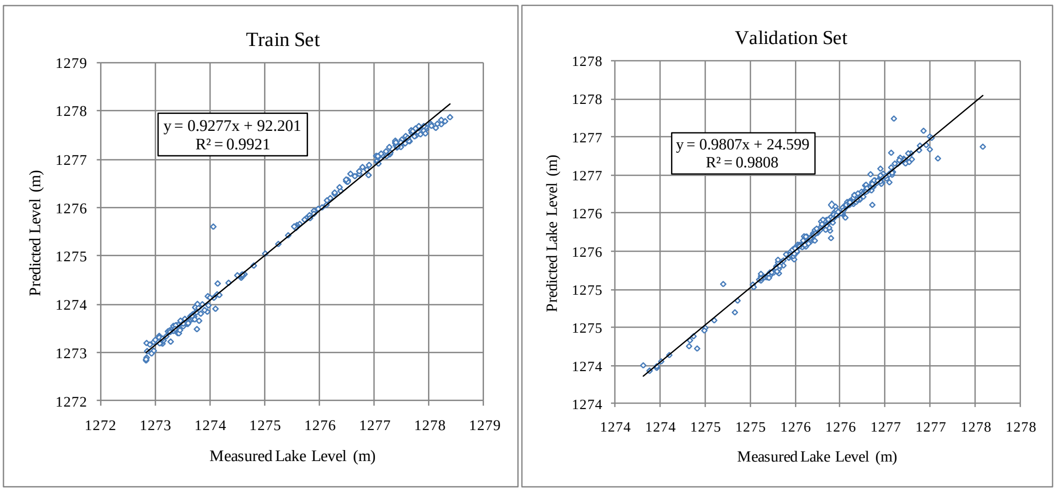

Fig. 9. Dispersion diagram of the MLP-1 (7 Neuron) results and observed data in the training and verification phases

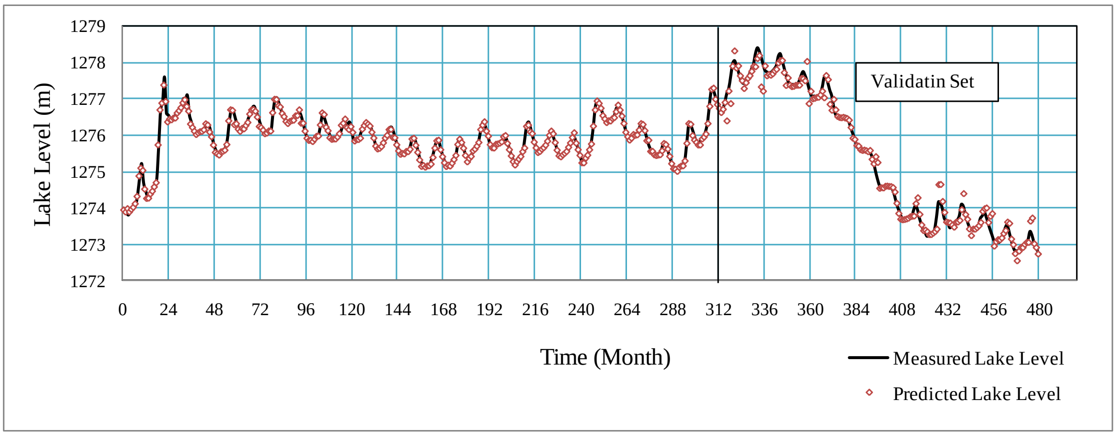

Fig. 10. Comparison of the obtained results using MLP-2 Model (12 Neuron) and observed data

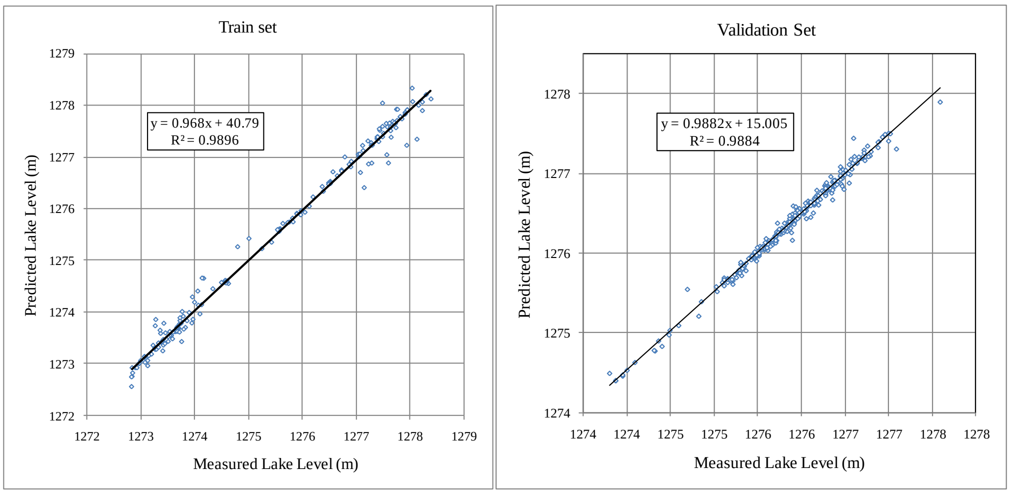

Fig. 11. Dispersion diagram of the obtained MLP-2 (12 Neuron) results and observed data in the training and verification phases

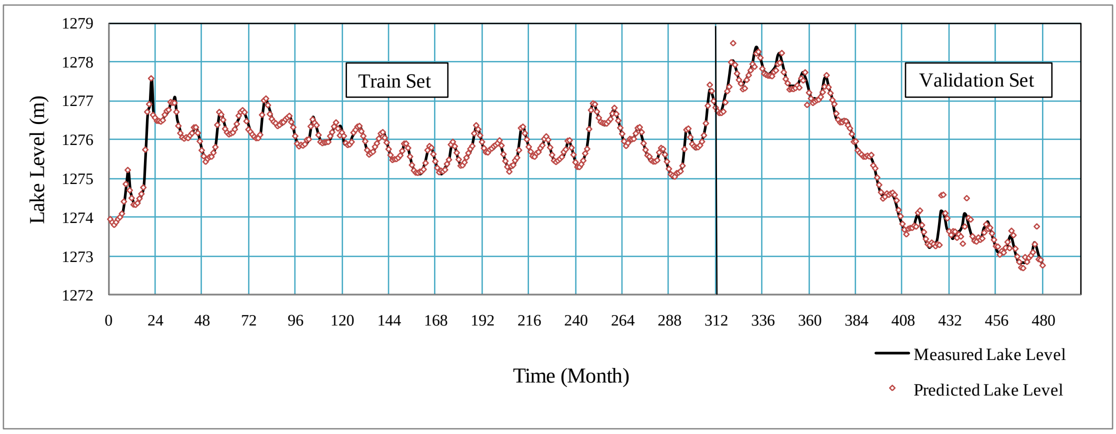

Fig. 12. Comparison of the obtained results using MLP-3 Model (14 Neuron) and observed data

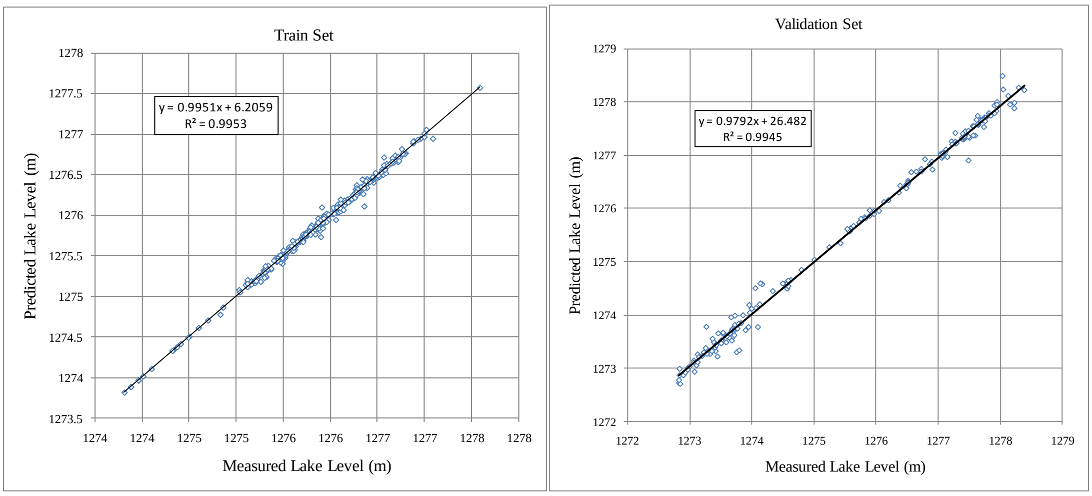

Fig. 13. Dispersion diagram of the obtained MLP-3 (14 Neuron) results and observed data in the training and verification phases

Different structures of the neuro-fuzzy models, numbers of inputs (which consists of inputs and their dynamics as well as outputs and their dynamic), number of rules and the divided algorithm or splits the main problem into smaller sub-problems, are given in Table 1. Meanwhile, Figs. 14 to 19, which are associated with Table 1, show graphical results of LLNF models in term of both line graphs and scatter plots.

In contrary to water balance model, the utilized Neuro-Fuzzy network has a proper function throughout the study period 1966-1967 till 2005-2006. In conclusion, it can be said that Neural-Fuzzy not only is an accurate model, but also is a reliable model even for periods that rarely recur.

The result of this method and two other studies are compared in Table 2.

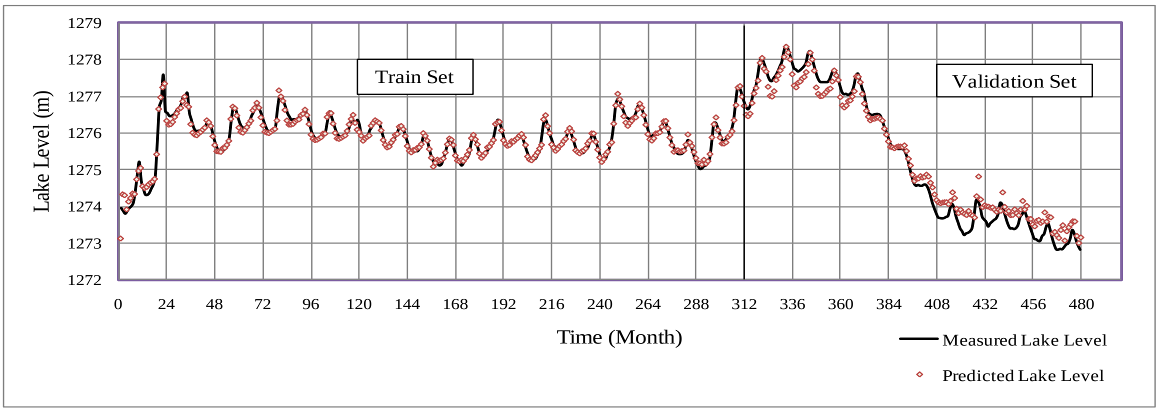

Fig. 14. Comparison of the obtained results using Neural-Fuzzy networks (5 Neuron) and the observed data

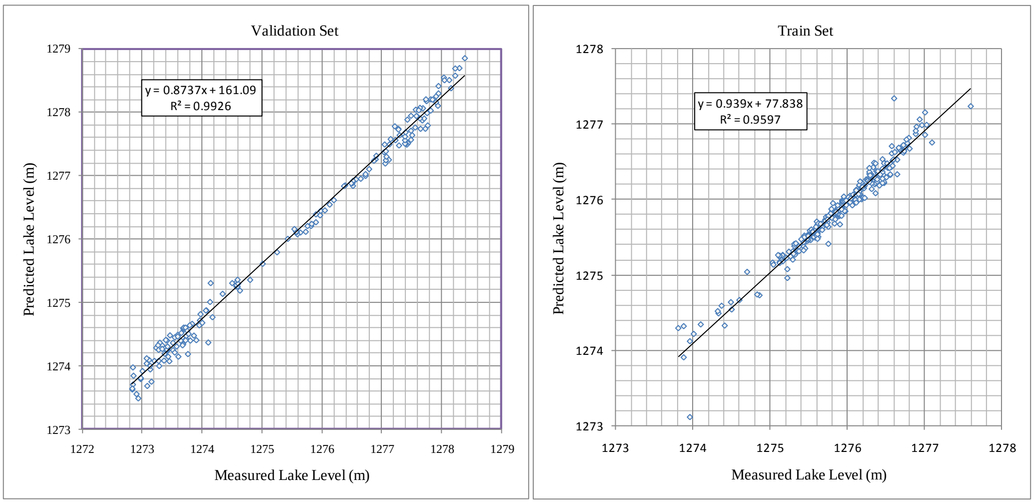

Fig. 15. Dispersion diagram of the Neural-Fuzzy networks (5 Neuron) results and the observed data in the training and verification phases

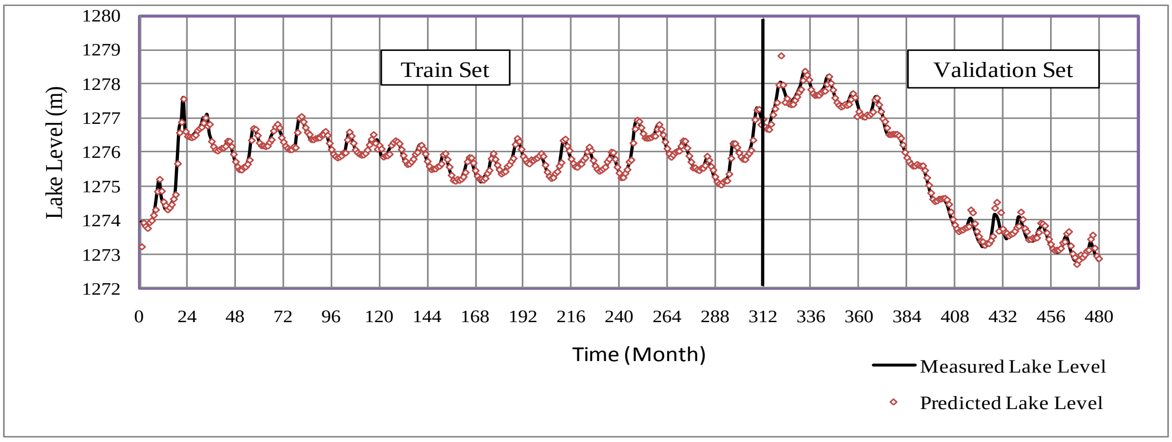

Fig. 16. Comparison of the obtained results using Neural-Fuzzy networks (8 Neuron) and the observed data

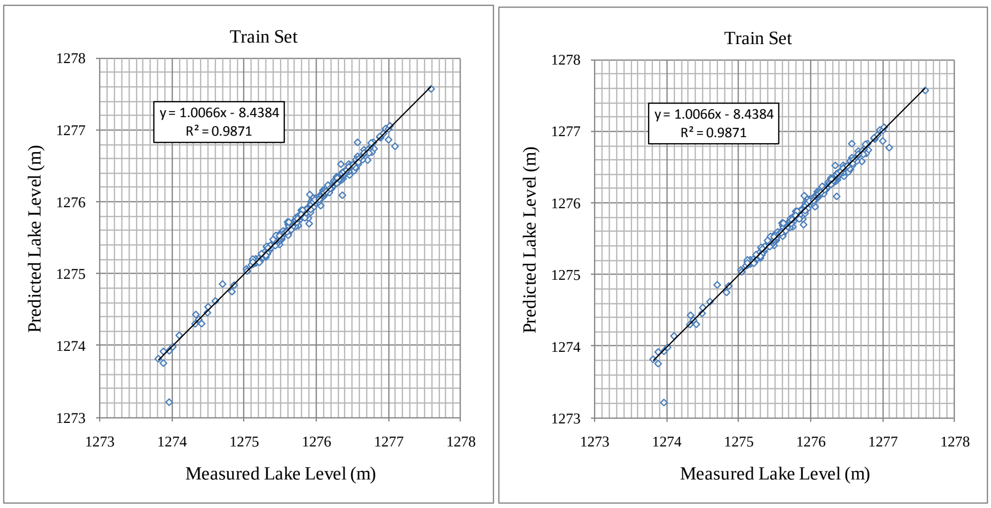

Fig. 17. Dispersion diagram of the Neural-Fuzzy networks (8 Neuron) results and the observed data in the training and verification phases

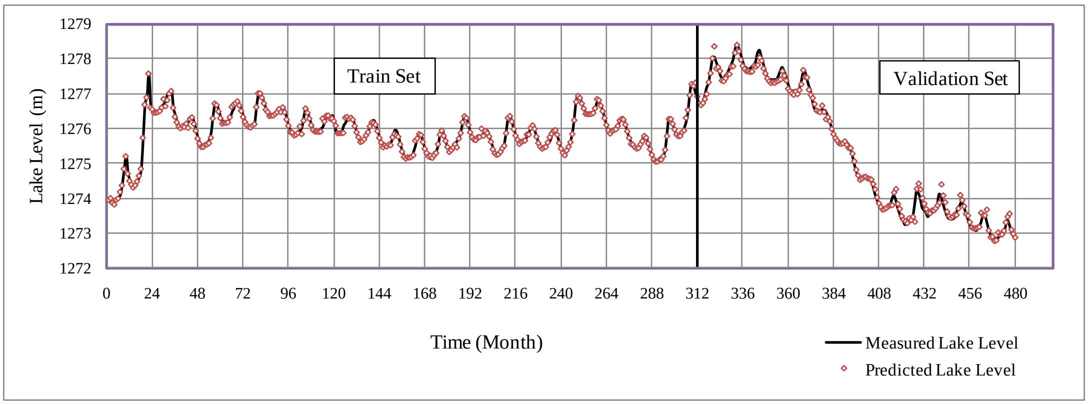

Fig. 18. Comparison of the obtained results using Neural-Fuzzy networks (11 Neuron) and the observed data

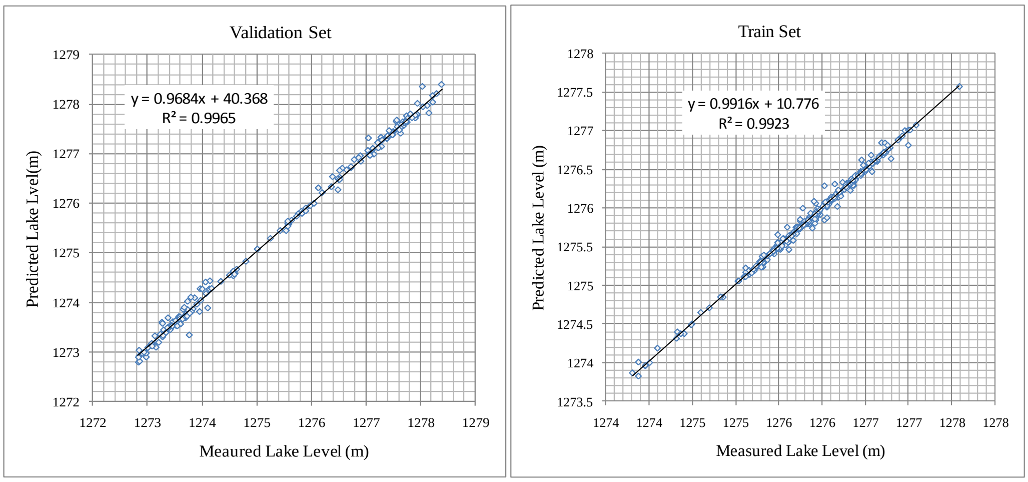

Fig. 19. Dispersion diagram of the Neural-Fuzzy networks (11 Neuron) results and the observed data in the training and verification phases

Table 2. Statistical comparison of the simulated monthly fluctuations of the water level in the Urmia Lake

Simulated methods \ Statistical parameters		index period(Month)	R^2	RMSE	Similarity
Water balance equation with 3 inputs (Pt, Qt, Et)		480	0.8534	0.486	0.6093
Neuro-Fuzzy Methods with 3 inputs in training phase (Pt, Qt, Et)		300	0.9923	0.0117	0.9962
Neuro-Fuzzy Methods with 3 inputs (Pt, Qt, Et) in verification phase		180	0.9965	0.109	0.9983
Traingin phase of neural network with 3 inputs (Qg ,Pt ,Qt ,Et)	Mohammadi et al.(2011)	30 years	0.9993	0.058	-
Verification phase of neural network with 3 inputs(Qg ,Pt ,Qt ,Et)		5 years	0.9826	0.062	-
Neural network with 3 inputs (Pt ,Qt ,Et)	Delawar et al. (2008)	348	0.9	0.26	-
Water balance equation		3	0.010	6.25	-

Table 3. Calculated performance by the Water balance and nonlinear models for the training and testing periods

Model	Training Set			Validation Set		
	RMSE(m)	Similarity(%)	R	RMSE (m)	Similarity(%)	R
Water balance	_	_	_	0.486	60.935	0.9234
MLP-1	0.08	86.16	0.9960	0.204	88.92	0.9903
MLP-2	0.065	89.183	0.9947	0.191	89.588	0.9941
MLP-3	0.042	93.06	0.9976	0.141	92.34	0.9972
DFM-1	0.042	92.994	0.9796	0.136	92.602	0.9962
DFM-2	0.024	96.069	0.9935	0.117	99.80	0.9979
DFM-3	0.017	99.62	0.9961	0.109	99.83	0.9982

Comparison of the statistical indices of the two proposed models, namely MLP and neuro-fuzzy models, and those obtained by the traditional water balance equation are presented in table 3. The results indicated that the neuro-fuzzy model causes more accurate results than the MLP and water balance equation.

In this study, comparison of the statistical indices of R between the Water balance equation and neural-fuzzy network indicated that estimation of the Lake water level had a significant performance.

In this research, due to the accurate collection of data from reliable sources and processing data, it expressed water balance equation had a better performance than the two other studies (Mohamadi et al., 2011, because of inappropriate conclusions, they only presented graphically in their paper). Moreover, the proposed neural-Fuzzy models in this research showed a better performance than the neural networks utilized in Delaware's studies. Mohamadi et al. (2011) used annual data for training and validation of their modeling. Accordingly, in the verification phase, only a given number of observed data were compared with the produced data. As mentioned before, the verification phase included a range of 180 data.

Because the problem was approximated by a number of simple linear sub-problems, the computational complexity of this method is less than the neural networks.

The purpose of this study and two similar researches mentioned before was modeling and prediction. However, in some cases the ultimate goal is to control modeled systems by using the obtained transfer function from the model. Finally, the neural network was expressed as a complex non-linear equation, therefore it is extremely complex and difficult to control. In contrast, in the locally linear method, the original nonlinear problem is expressed as a set of non-linear sub-problems. Therefore, the linear control rules can be used that are much easier to adjust the system performance.

A final note on the use of locally linear model and the Neuro-Fuzzy networks versus the neural networks is that model can be written as T-S fuzzy models. Thus, if required, it can be considered as a set of Fuzzy IF-THEN rules.

6. Conclusions

In this research, more statistical periods and data were used in comparison to the previous studies to simulate Lake water level fluctuations in the balance model and neural fuzzy system. An important reason for high correlation coefficient in the balance equation in this study was that more complete data was used particularly considering the monthly flow of all the entering rivers to the Lake and monitoring data. Although there was a high correlation coefficient in the balance method in this research and there was a conformity to the observed data, which was obtained from the water level changes, however by using the fuzzy neural networks (if properly trained) it would be possible to accurately estimate the Lake water level fluctuations (R=0.9982).

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