

Using Neural Network Models to Forecast the Inflow of Doroudzan Dam – Iran

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INTRODUCTION

Iran with an average annual rainfall of 230 mm is in the categories of semi-arid countries. Using water and optimizing exploitation of water sources has always been considered. Therefore many dams are built to control water in Iran. One of the most important dams in the south of Iran, in Fars province, is Doroudzan dam which has an important role as the water provider for the biggest center of wheat production in Iran. Scheduling to have optimum water exploitation of this resource necessitates realistic forecasting of inflow to the dam reservoir. One of the methods to forecast inflow to the reservoirs is to use neural network models which are considered in this paper. In this study Qnet 2000 computer model is used and its results are presented for practical applications.

NEURAL NETWORK

A human brain continually receives input signals from many sources and processes them to create the appropriate output response. Our brains have billions of neurons that interconnect to create elaborate “neural networks”. These networks execute the millions of necessary functions needed to sustain normal life. For some years now, researchers have been developing models, both in hardware and in software, that mimic a brain’s cerebral activity in an effort to produce an ultimate form of artificial intelligence. Many theoretical models (or paradigms), dating as far back as the 1950’s, have been developed. Most have had limited real-world application potential, and thus, neural networks have remained in relative obscurity for decades. The backpropagation paradigm, however, is largely responsible for changing this trend. It is an extremely effective learning tool that can be applied to a wide variety of problems. Backpropagation related paradigms require supervised training. This means they must be taught using a set of training data where known solutions are supplied. Backpropagation type neural networks process information in interconnecting processing elements (often termed neurons, units or nodes— we will use “nodes”). These nodes are organized into groups termed layers. There are three distinct types of layers in a backpropagation neural network: the input layer, the hidden layer(s) and the output layer. A network consists of one input layer, one or more hidden layers and one output layer. Connections exist between the nodes of adjacent layers to relay the output signals from one layer to the next. Fully connected networks occur when all nodes in each layer receive connections from all nodes in each preceding layer. Information enters a network through the nodes of the input layer. The input layer nodes are unique in that their sole purpose is to distribute the input information to the next

processing layer (i.e., the first hidden layer). The hidden and output layer nodes process all incoming signals by applying factors to them (termed weights). Each layer also has an additional element called a bias node. Bias nodes simply output a bias signal to the nodes of the current layer. Qnet handles these bias nodes automatically. They do not need to be included or specified by the user. All inputs to a node are weighted, combined and then processed through a transfer function that controls the strength of the signal relayed through the node's output connections. A nodes operation is shown in figure 2 below. The transfer function serves to normalize a node's output signal strength between 0 and 1 Qnet provides four transfer functions: the sigmoid (default), gaussian, hyperbolic tangent and hyperbolic secant functions. Qnet allows the transfer function to be selected on a layer-by-layer basis to create unique hybrid networks. Network processing continues through each layer until the network's response is obtained at the output layer. When a network is used in recall mode, processing ends at the output layer. During training, the network's response at the output layer is compared to a supplied set of known answers (training targets). The errors are determined and backpropagated though the network in an attempt to improve the network's response. The nodal weight factors are adjusted by amounts determined by the training algorithm. The iterative procedure of processing inputs through the network, determining the errors and backpropagating the errors through the network to adjust the weights constitutes the learning process (Winnetka 1999).

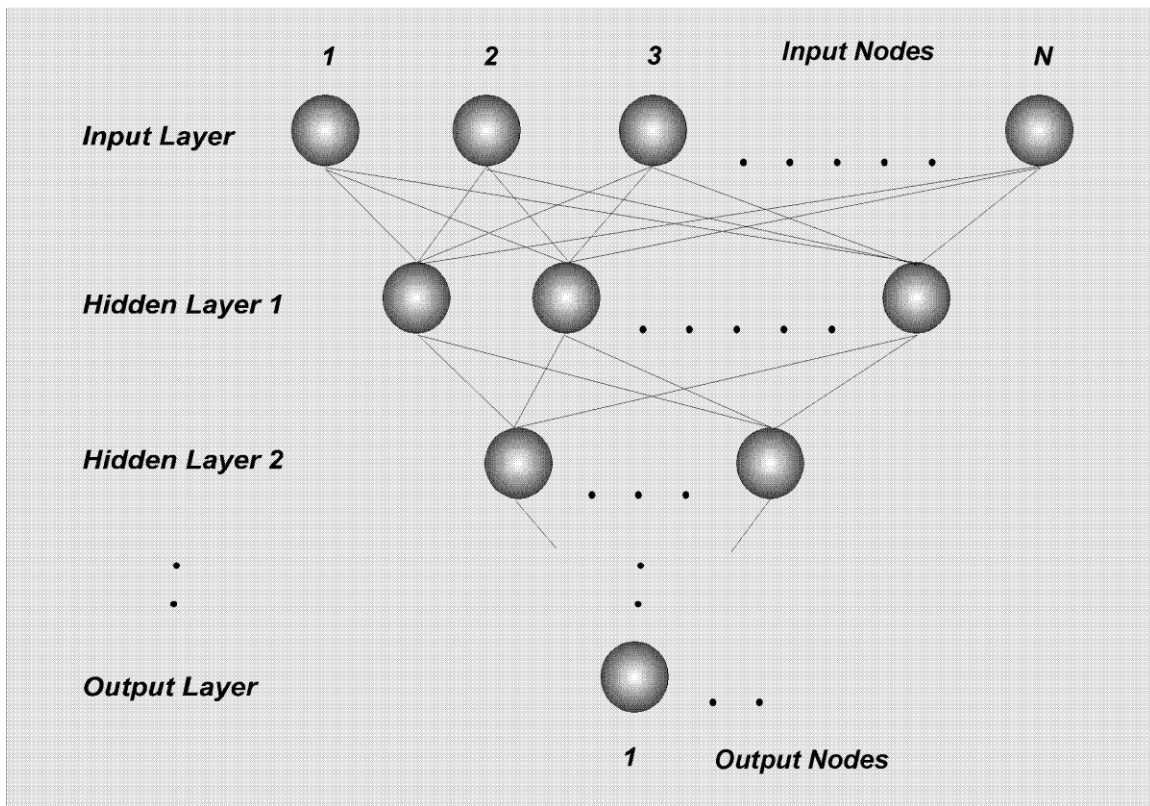


Figure (1): Neural Network Design Topology

One training iteration is complete when all supplied training cases have been processed through the network. The training algorithms adjust the weights in an attempt to drive the network's response error to a minimum. Two factors are used to control the training algorithm's adjustment of the weights. They are the "learning rate coefficient", eta, and the "momentum factor", alpha. If the learning rate is too fast (i.e., eta is too large), network training can become unstable. If eta is too small, the network will learn at a very slow pace. The momentum factor has a smaller influence on learning speeds, but it can influence training stability and promote faster learning for most networks. Qnet uses a sophisticated control scheme that adjusts the learning rate coefficient to keep network training proceeding at a near optimal pace.

Neural networks are flexible mathematical models which can be used in simulation of river flow. The prediction of flow into a reservoir is fundamental in water resources planning and management. Prior knowledge of the arrival of flood can be used to route the flood safely through the reservoir. This reduces the danger of flood damage at the downstream region and ensures safety of the dam. Therefore, the need for timely and accurate streamflow forecasting is widely recognized and emphasized by many in water resources fraternity. Real-time forecasts of natural inflows to reservoirs are of particular interest for operation and scheduling. A variety of methods have been proposed for this purpose including conceptual (physical) and empirical models, but none of them can be considered as unique superior model (ASCE 2000). Owing to difficulties of formulating reasonable non-linear watershed models, recent attempts have resorted to Neural Network (NN) approach for complex hydrologic modeling (Coulibaly et al. 2000).

CASE STUDY

Doroudzan dam

The multipurpose earth fill Doroodzan dam is located some 85 km. North West of Shiraz on Kor River and in the Bakhtegan lake catchment area. Doroudzan dam studies and investigation were carried out in the years 1963 to 1966 and the dam construction was started in 1970 and was complicated in 1974. The consulting engineer was Justin & Courtney jointed with Taleghani & Daftari. The contractor was WRD.

The objectives of constructing Doroodzan dam are as follows (Torabi Haghghi 2004):

- 1) Irrigation water supply for 110/000 ha.
- 2) Supplying parts of urban water needs for the cities of Marvdasht and Shiraz.
- 3) Supplying industrial water needs of the nearby factories.
- 4) Flood control of Kor River.
- 5) Energy generation.

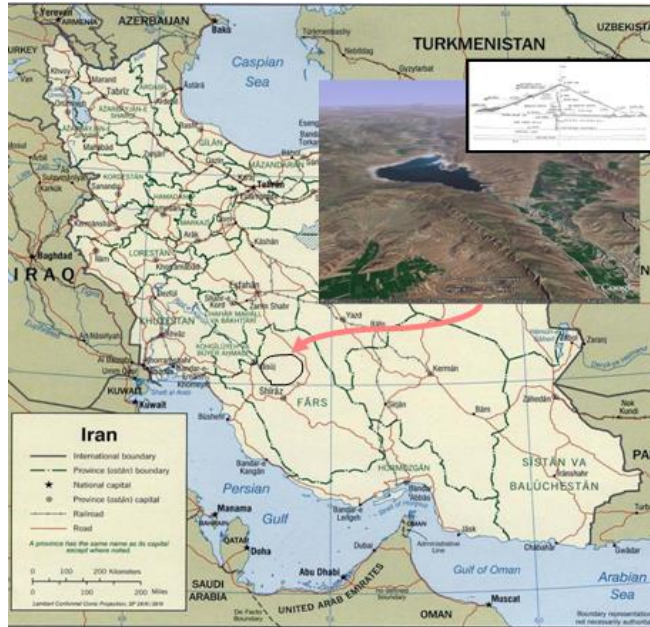


Figure (2): Doroudzan Dam Location

Technical data

Dam type:	Homogeneous embankment with riprap protection.
Height	57 m.
Crest length	710 m.
Crest width	10 m.
Crest elevation	1683.5 mcl
Max width at base	375m.
Fill volume	4.8 MCM.
Foundation	limestone rock.
Volume	993 MCM
Surface at normal water level	55 Km ²
Dead storage	133 MCM
Spillway type	ojee spillway (with Design flood 3000 cms)
Design flood	3000 cms
Catchment area	4372 km ²
Mean annual river flow to the reservoir	1192MCM.
Mean annual evaporation from the reservoir	64 MCM.
Mean annual precipitation	485mm

The importance of forecasting inflow to Doroudzan dam

Forecasting inflow to Doroudzan dam has always been one of the main programs of water resource managers of this dam and can be considered in some aspects:

- Planning for exploitation of water resources in future
- Planning for the years with water shortage (preventing drought)
- Planning to save water in excess of use and change it to energy in wet years.
- Planning to determine consumption patterns and generating energy

These forecasts can be made for different durations. Short time forecasting for duration less than one week, middle time for monthly and seasonal forecasting and long time for annual forecasting. Planning for the dams in Iran is made on the basis of water year which starts from December until next September.

Most of the water storage in Doroudzan dam is used in supplying agriculture needs. Determining the amount of subculture area of agriculture products in each year has many problems because the beginning of cultivation of wheat and barley which include most of the agriculture products of the region is in autumn and it's in the same time with the beginning of rainfall season so there is not any information about available inflow water to determine the subculture area.

If the water needs of subculture area would be more than available water, supplying water for the lands faced with problems and if subculture area would be limited, in the case of wet year some water amounts should be evacuated through the dams outlets without any use and on the other hand reduction of subculture area reduces the amounts of agricultural products. Therefore estimating the annual inflow in the beginning of water year is too important to determine the optimal subculture area.

Suitable rainfall during winter can fill the reservoir and make it to overflow in the end of winter and losing great amount of water which has been happened so many times in recent years. Forecasting the reservoir condition, the excess water in winter can be conducted to generate energy before overflowing the dam so forecasting inflow especially seasonal forecasting for winter is too important. In this research in addition to estimating seasonal inflow, annual, weekly and daily inflow is considered.

Statistics, information and variables used in models

Achieving suitable neural network models, available statistic must be used. According to research the information which is used includes daily, weekly, monthly and annual inflow to the dam in dam and upstream station, the daily, weekly, monthly and annual rainfall data in dam station, the data related to The Southern Oscillation is the difference in sea-level atmospheric pressure between the island of Tahiti and Darwin, Australia. A negative Southern Oscillation Index (SOI) is associated with slackening of easterly winds (westward-blowing), allowing the western warm pool (WWP) -centered east of Indonesia, the world's "hot spot" -to shift to the east. A negative SOI is thus associated with an El Niño event, in which anomalously warm water reaches the west coast of South America. This usually occurs around Christmas time, thus the event has been dubbed El Niño, or "The Christ Child". El Niño events affect the jet stream and are statistically

related to extreme weather events in specific areas of the globe (Kiladis and Diaz 1989; Glantz et al. 1991). As exam-ples, Northeast Brazil usually experiences drought, while southeast Brazil and Peru experience heavy rains and often flooding. Southern Africa has a strong "signal," and usually experiences drought. The Southern Oscillation Index was introduced for the first time by walker in 1923 which its effects can be considered in the case of drought or flood. In this research more than 65000 data was used (Torabi Haghghi 2003).

Used models

Using the mentioned data, different combinations of neural network models were prepared. Tables 1 to 5 shows combination of different parameters which are used in each model for daily, weekly, monthly, seasonal and annual forecasting. Considering amounts of data, 80% of data was used for training the model and 20% for testing the model. Evaluating the models, with parameter combination as mentioned in table 6, selected models were recognized. Correlation results of best models, in each case of training model is presented in figure 3 to 7.

number models	<i>Parameters which are used in daily models</i>													RESULT	
	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5	p-6	weekly	train	test
1	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5	p-6	weekly	93%	91.5
2	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5		weekly	92	90
3	q-1	q-2	q-3	q-4	q-5		p-1	p-2	p-3	p-4	p-5	p-6	weekly	92	89.5
4	q-1	q-2	q-3	q-4			p-1	p-2	p-3	p-4	p-5		weekly	91	89
5	q-1	q-2	q-3	q-4	q-5		p-1	p-2	p-3	p-4			weekly	91	89
6	q-1	q-2	q-3	q-4			p-1	p-2	p-3	p-5			weekly	90	88
7	q-1	q-2	q-3				p-1	p-2	p-3				weekly	91	88
8	q-1	q-2					p-1	p-2					weekly	93	89
9	q-1						p-1	p-2					weekly	91	88
10	q-1						p-1						weekly	90	88
11	q-1												weekly	87	83
12	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5	p-6		91%	89%
13	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5			90	88%
14	q-1	q-2	q-3	q-4	q-5		p-1	p-2	p-3	p-4	p-5	p-6		89	86.5
15	q-1	q-2	q-3	q-4			p-1	p-2	p-3	p-4	p-5			88	85
16	q-1	q-2	q-3	q-4	q-5		p-1	p-2	p-3	p-4				88	85
17	q-1	q-2	q-3	q-4			p-1	p-2	p-3	p-5				89	86
18	q-1	q-2	q-3				p-1	p-2	p-3					88	84
19	q-1	q-2					p-1	p-2						85	83
20	q-1						p-1	p-2						86	84
21	q-1						p-1							87	85
22	q-1													85%	80%
q-1: inflow with 1 day delay,q-2 inflow with 2 day delay, q3 inflow with 3 dates delay,...															
p-1:daily rainfall with 1 day dlay,p-2 idaily rainfall with 1 day dlay,, weekly result model															
weekly : weekly result of best model															

Table (1): Parameters which are used in daily models

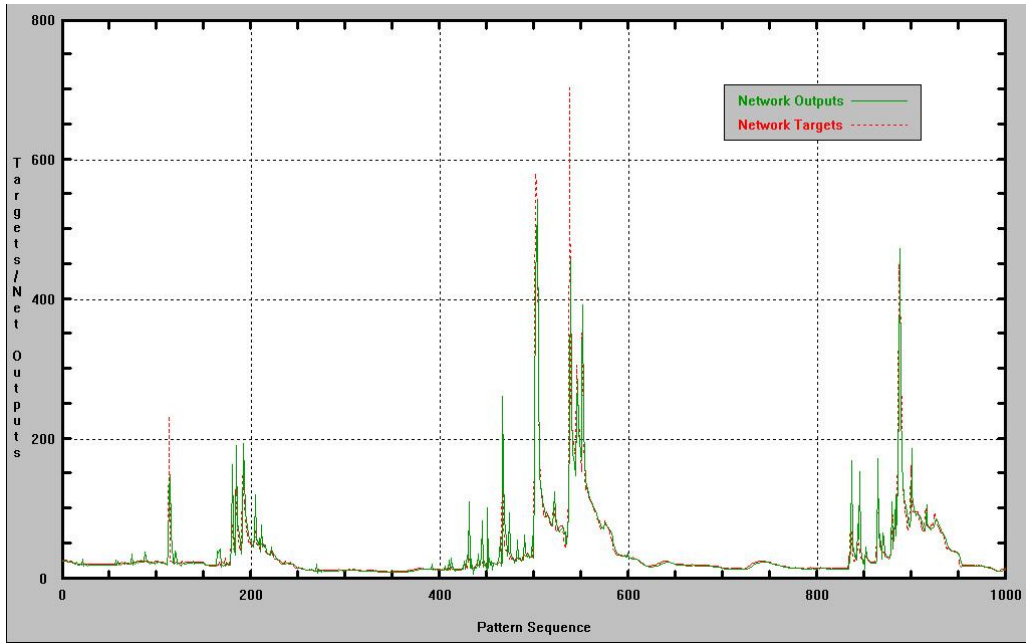


Figure (3): Output of Daily ANN Models for Doroudzan Dam Inflow

number models	<i>Parameters which are used in weekly models</i>								RESULT	
	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	train	test
23	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	95	92.5
24	q-1	q-2	q-3	q-4	q-5	q-6	p-1		94	91
25	q-1	q-2	q-3	q-4	q-5		p-1	p-2	93	90
26	q-1	q-2	q-3	q-4			p-1	p-2	94	92
27	q-1	q-2	q-3	q-4	q-5		p-1		93	91
28	q-1	q-2	q-3	q-4			p-1		92	90.5
29	q-1	q-2	q-3				p-1	p-2	91	88
30	q-1	q-2	q-3				p-1		89	87

q-1: inflow with 1 day delay, q-2 inflow with 2 day delay, q3 inflow with 3 dayes delay, ...
p-1: weekly rainfall with 1 week dlay, p-2 weekly rainfall with 2 week dlay,

Table (2): Parameters that used in weekly models

number models	<i>Parameters which are used in monthly models</i>					RESULT		
	q-1		p-1	p-2	p-3	train	test	
31	q-1		p-1	p-2	p-3	73	71	
32	q-1		p-1	p-2		70	68	
33	q-1		p-1			65	63	
34	q-1					60	55	
35	q-1		p-1	p-2		soi	71	69
36	q-1		p-1	p-2	0	soi	66	64

q-1: inflow with 1 month delay,
p-1: monthly rainfall with 1 month dlay, p-2 monthly rainfall with 2 month dlay,,
soi Southern Oscillation Index elnino parameter

Table (3): Parameters which are used in monthly models

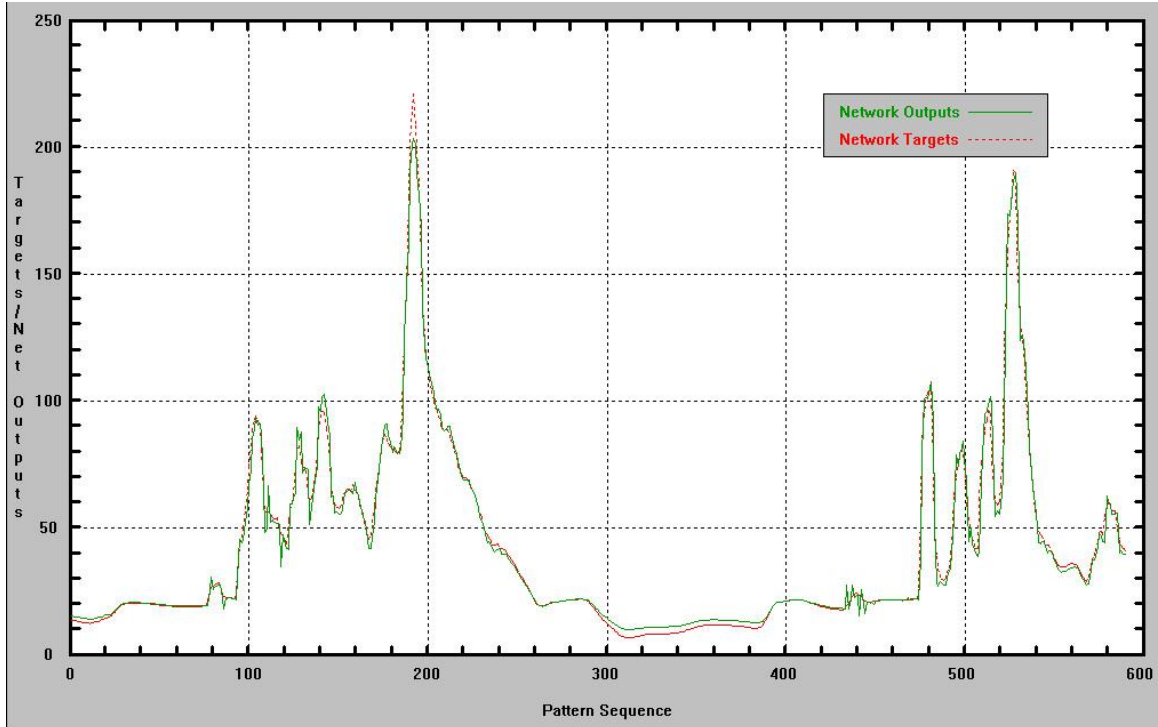


Figure (4): Output of weekly ANN Models for Doroudzan Dam Inflow

number models	<i>Parameters which are used in seasonal models</i>					RESULT	
						train	test
37	q-1	p-1	p-2	p-3		54	52
38	q-1	p-1	p-2			45	43
39	q-1	p-1				38	35
40	q-1					30	27
41	q-1	p-1	p-2		soi	60	56
42	q-1	p-1	p-2	p-3	soi	55	52
q-1: inflow with 1 season delay,							
p-1: seasonal rainfall with 1 month delay, p-2 seasonal rainfall with 2 month delay,							
soi Southern Oscillation Index elnino parameter							

Table (4): Parameters which are used in seasonal models

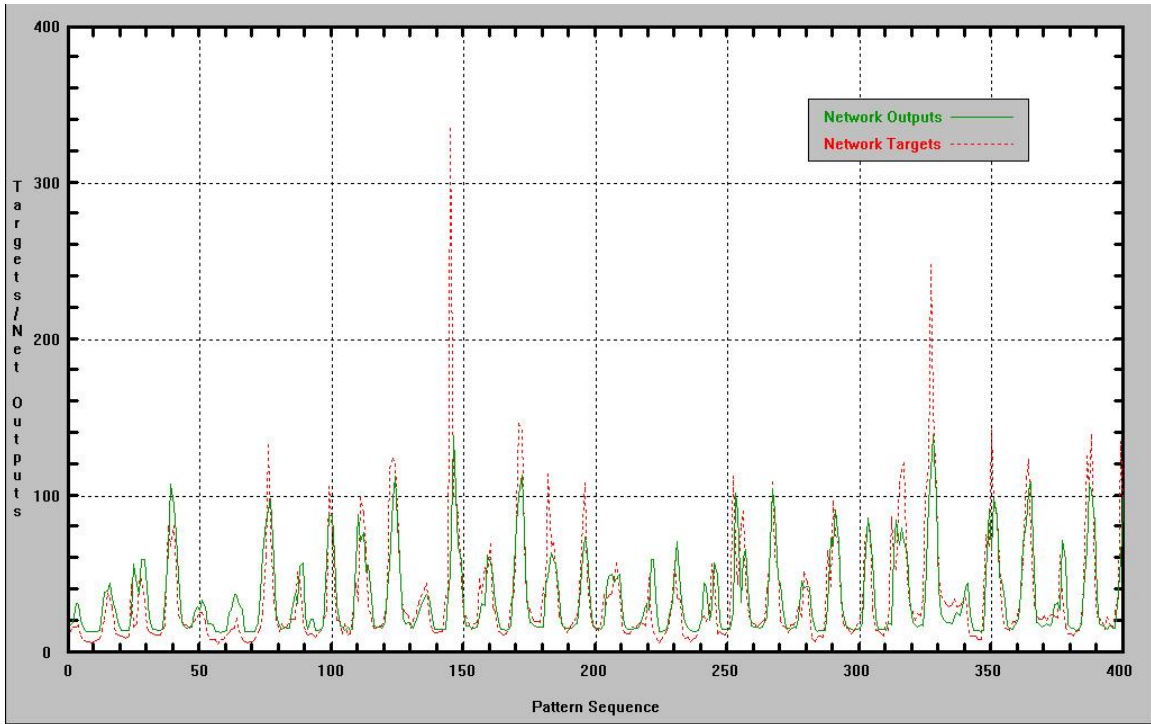


Figure (5): Output of monthly ANN Models for Doroodzan Dam Inflow

number models	<i>Parameters which are used in yearly models</i>					RESULT	
						train	test
43	q-1	p-1	p-2	p-3		79	77
44	q-1	p-1	p-2			78	76
45	q-1	p-1				35	33
46	q-1					30	27
47	q-1	p-1	p-2		soi	79	77
48	q-1	p-1	p-2	0	soi	78	76
q-1: inflow with 1 year delay,							
p-1: yearly rainfall with 1 year delay, p-2 yearly rainfall with 2 year delay,							
soi Southern Oscillation Index elnino parameter							

Table (5): Parameters that used in yearly models

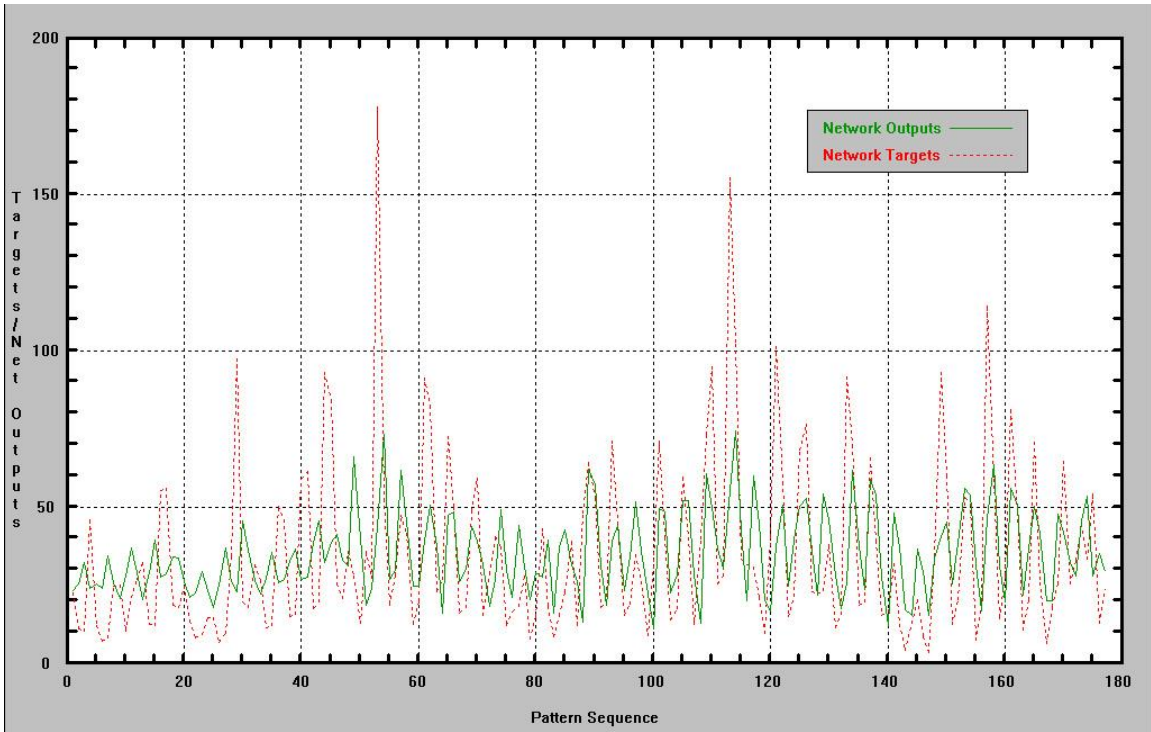


Figure (6): Output of seasonal ANN Models for Doroodzan Dam Inflow

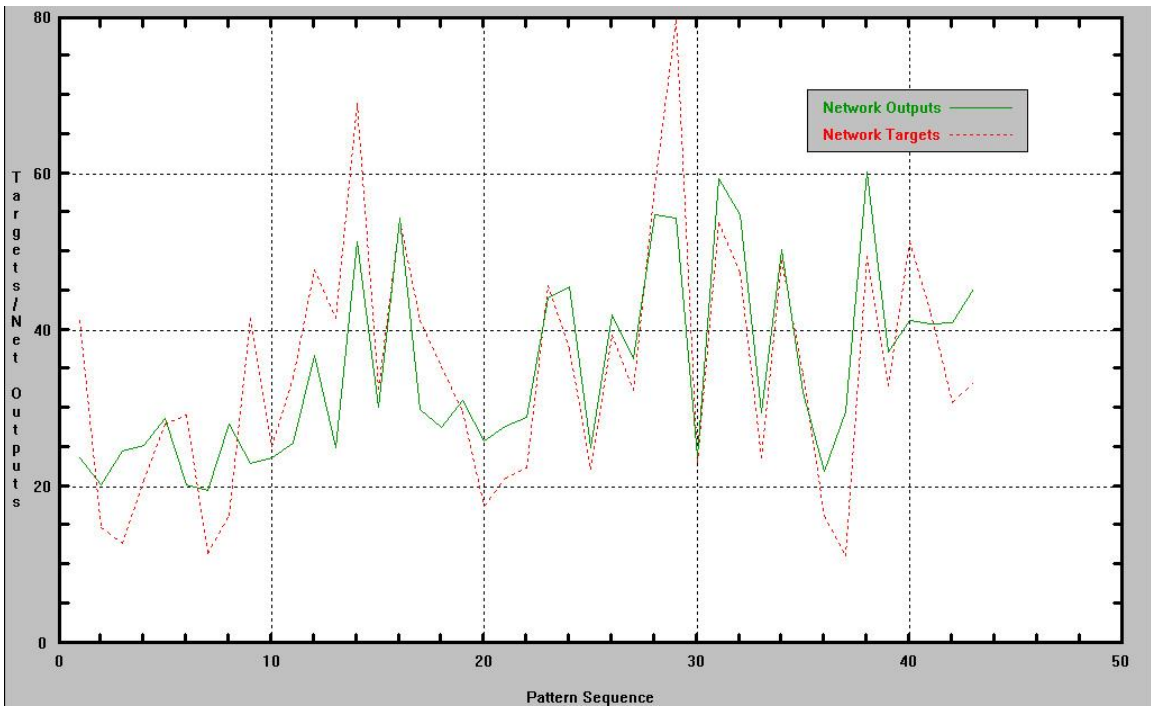


Figure (7): Output of weekly ANN Models for Doroodzan Dam Inflow

number models	Parameters that used in each models													RESULT	
	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2	p-3	p-4	p-5	p-6	daily	train	test
1	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2					daily	93%	91.5
23	q-1	q-2	q-3	q-4	q-5	q-6	p-1	p-2					weekly	95%	92.5
31	q-1						p-1	p-2	p-3				monthly	73%	71
41	q-1						p-1	p-2				sol-1	seasonal	60%	56
47	q-1						p-1	p-2	0			sol-1	yearly	79%	77

Table (6): Best Ann Models in each case

Discussion

As it was discussed, due to exploitation of Doroudzan dam reservoir, forecasting the inflow can help flood control, generating energy and determining optimized subculture area so to forecast the inflow to Doroudzan dam using neural network model some neural network models was provided. Creating different models *Qnet* software was used and forecasting annual, seasonally, monthly, weekly and daily inflow 47, 23, 31, 41 and 14 neural network models respectively were used. Some data like daily, weekly, monthly, seasonal and annual inflow to reservoir, rainfall and the data related to elnino were used in these models. The models were prepared with the combination of mentioned parameters and different time delays by *Qnet* software. Finally some models had better results beside the others which can be presented models no. 1, 23, 31, 41 and 43 as chosen model to forecast daily, weekly, monthly, seasonal and annual inflow respectively. As it is seen, the best adaptation is related to weekly inflow models, which can help the energy generation program. Monthly and seasonal models regardless of less correlation beside weekly models can be used to plan energy generation from January to April and can be used to determined subculture area.

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