Trend Analysis of Water Inflow Into The Dam Reservoirs Under Future Conditions Predicted By Dynamic NAR And NARX Models

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Abstract

Nowadays, the use of artificial intelligence is extended to various scientific and engineering fields including water management and planning. This study investigates the performance of dynamic artificial neural network (ANN) models in prediction of water inflow into the Sefidrud dam reservoir (Iran). For this purpose, first, the discharge time series of tributaries of the Sefidrud dam are analyzed for trends for a 47 year time period (1345-1392) using parametric regression and non-parametric Mann-Kendall tests considering independence, short-term, and long-term persistence assumptions. Also, the homogeneity of the data is investigated using three statistical tests including Cumulative Deviations, Worsley's Likelihood Ratio, and Bayesian inference. Then, the inflow discharges into the reservoir of Sefidrud dam from GhezelOzan and Shahroud tributaries are simulated using dynamic Nonlinear Auto-Regressive (NAR) and Nonlinear Auto-Regressive with exogenous input (NARX) models. Further, water inflow values of both rivers are predicted for the next 5 years in future using dynamic NAR and NARX models. Finally, the obtained results are investigated using trend analysis approach. Obtained results show a significant decreasing trend in both rivers. Results also show a continuous downward trend for the following 5-year period predicted by NAR and NARX models. In addition, it was found that the results obtained by the NARX model are less accurate compared to those by the NAR model.

1. Introduction

The increasing consumption of surface and groundwater resources in Iran coincided with global climate change has led to increasing pressure on the existing water resources. Therefore, without comprehensive attention to the existing limitations and challenges, sustainable planning and management of water resources will not be possible in Iran, which is located in the arid and semi-arid regions of the world. Lack of appropriate frameworks and laws, inefficient operation of the available water resources, excessive consumption of groundwater resources, and the intensified pollution are some of serious challenges with respect to water resources management in Iran. Therefore, it is important to regenerate and update the existing frameworks in order to provide the necessary conditions for optimal operation of the limited resources.

Generally, any permanent change in the climate patterns, whether regionally or globally, is called "climate change". Throughout the life of the planet, climate has been changing continuously. However, in recent decades, there have been far greater and more significant changes than what have ever been recorded before. The recent research works show the crucial impact of climate change on trends in climatic and hydrological variables (Ehsanzadeh and Adamowski, 2010). In general, extensive changes in precipitation and temperature patterns are known to be the driving forces of these changes. In other words, increased temperature leads to intensified evaporation from moist surfaces and this in turn leads to more humidity in the atmosphere. Increased humidity in the atmosphere leads to intensified hydrologic cycle which causes massive floods in some areas and extensive droughts in other regions. In addition, reviewing previous numerous research works indicate that changes in the melting history of snow and its inclination in winter lead to a considerable change in flow patterns of rivers in different parts of the world. One of the most important impacts of this phenomenon on water resources in Iran and some other regions of the world is the reduction of precipitation in the form of snow and the shift of snowmelt timing towards the cold seasons. This leads to reduction of river flow in the spring and summer and therefore water inflow into the dam reservoirs are inconsistent with the values considered at the time of design. Efficient and reliable planning of water resources is impossible without considering the effects and consequences of climate change phenomenon. In other words, the occurrence of such changes in the future leads to the problematic management of water resources which is based on the assumption of stationary hydrology (Middle Cope et al., 2001). In near future, this issue is one of the most important challenges for planning and management of water resources, and therefore operation policies should be updated and modified according to new conditions (Steele-Dunne et al., 2008).

In recent years, numerous studies have been performed in the field of climate change and its effects on water resources systems and hydrological variables. The results of these researches indicate the gradual changes of climatic conditions for different regions of the world, including Iran (Dudangeh et al., 2010; Pirnia et al., 2015). The climatic instabilities lead to uncertain determination of design parameters, which is one of the main challenges in water resources engineering (Xu et al., 1997).

For solving reservoir operation problems, different uncertain and unstable variables should be considered including water inflow into the reservoir and downstream water demand under future conditions. Using realistic values or at least appropriate estimated values of these variables taking into account climate instability impact on these variables can lead to a significant improvement of the reservoir operation performance (Loucks et al., 1981). For optimal operation of reservoirs, therefore, it is necessary to consider the impact of the mentioned uncertainties and possible instabilities (Soleimani et al., 2016).

One of the simplest and most practical methods to study climate variations and changes in hydrological data is to study the trends of hydrological and climatic variables. From a statistical and climatic point of view, the values of decreasing or increasing trends for variables such as precipitation, runoff, and evaporation can be attributed to increasing trend of average temperature at the Earth's surface.

Statistical tests are commonly used to determine hydrological trends. In general, statistical tests are divided into two categories of parametric and non-parametric tests. Non-parametric tests are superior to parametric tests because no information on the probability distribution of data is required (Rood et al., 2005). The most common non-parametric tests for trend analysis are Mann-Kendall and Spearman tests, which have been widely used in recent years to study trend in climatic variables (Burn & Elnur, 2002; ZarehAbyaneh et al., 2011; Pirnia et al., 2015; Azarakhshi et al., 2013; Asakereh and Doostkamian, 2014).

One of the limitations of classical statistical trend tests is the assumption of data independence and lack of storage capacity (Ehsanzadeh and Adamowski, 2010). If a short-term or long-term correlation is observed among the data, the mentioned assumptions are problematic. Since serial dependencies or short-term persistence (STP) are observed in most hydrological and climatic time series, statistical tests should be revised to account for this phenomenon (Ehsanzadeh and Adamowski, 2010). In 1951, Hurst observed long-term serial correlation among some time series, known as Hurst phenomenon (Hurst, 1951). This phenomenon which shows long term correlation among time series can affect the results of trend detection studies (Fathian et al., 2014). The intensity of the Hurst phenomenon or long-term persistence (LTP) for time series is measured using the Hurst exponent (H). If long-term persistence is detected in climate and hydrological data, its impact on statistical analysis of data should be considered.

For most hydrological designs, the homogeneity of climate data is very important. However, it is often observed that climate data are heterogeneous (Buishaund, 1982). In many studies, in addition to analysis of trends, the homogeneity of time series have also been investigated (Modaresi et al., 2010). Generally, heterogeneity in hydrological data can be caused by various factors including climate change. The heterogeneity of time series affects the results of a meaningful trend detection of a specific variable. Various tests such as statistical tests of Cumulative Deviations, Worsley's Likelihood Ratio Test, and Bayesian inference have been proposed and used to investigate the existence of heterogeneity in the time series.

A wide range of different factors affects river flows at different times of the year including climatic variables, physical, and geometric characteristics of the upstream basin condition, and the amount of upstream water allocation. The degree of extensiveness and variability of these factors leads to the uncertain discharges of rivers. Climate change due to increased greenhouse gases, on the other hand, enhances the mentioned uncertainty

Reviewing past researches in the field of reservoir operation shows that the amount of water allocated to a user or released from a reservoir is determined using the measured inflow to the reservoir in previous years. This management practice leads to unfavorable results due to changes in inflows over time. In other words, one of the most important parameters for water resources management is predicting the true amounts of inflows and outflows in the future. For this purpose, various methods have been proposed that can be generally classified into two categories: data-driven methods and conceptual methods. In data-driven methods, the modeler relies only on runoff time series and maybe precipitation and temperature to predict inflow. Conceptual methods, however, are based on the accurate comprehension of the physical mechanisms governing the hydrological processes of the basin. Therefore, conceptual methods require a wide range of hydrological and meteorological data of the basin for modeling and predicting the flow. Less dependence of data-driven methods on the volume of input data, as well as less complexity of these methods, has led to greater popularity of these models (Lima et al., 2014).

Data-driven models are more commonly used in recent years due to some specific features of these models (Takeuchi and Sivaarhithkul, 1995; Faber and Stedinger, 2001; Chiew et al., 2003; Maurer and Letnmeier, 2004; Dong et al., 2005; George Jacques and Graham, 2008; Madsen et al., 2009; Tang et al., 2010; Ahmadi et al. 2014; Zhao et al., 2015 and Arena et al., 2015). One of the most usual data-driven models is the artificial neural network (ANN) model. The ANN models are applied for solving various engineering problems including water resources engineering problems. So far, a wide range of different combinations of input variables, network structures and frameworks, and various training algorithms have been used in ANN modeling. ANN models are powerful computational methods that are capable of identifying and finding complex relationships between hydrological and climatic variables, leading to relatively accurate predictions. It is worth noting that modeling hydrological processes is difficult but extremely important. The complex and dynamic nature of hydrological processes makes the use of intelligent and nonlinear models such as ANN models inevitable. Generally, ANN models are divided into two general categories: static and dynamic or recursive networks (Gómez-Ramos and Wongas-Martinez, 2013). Reviewing the researches shows that ANN models, especially dynamic ANNs are widely used in different fields of water engineering problems (Daniell,

1991; French et al., 1992; Hall and Minns, 1993; Hsu et al., 1995; Hamlet et al., 2002; Lin and Chen, 2005; Cigizoglu, 2008; Hung et al., 2009; Shen and Chang, 2013; Ruslanet al., 2013; Rani and Parekh, 2014; Banihabib et al., 2014; Yin et al., 2014; Zhe et al., 2015).

Although accurate flow prediction improves the efficiency of water resources management policies, so far no comprehensive approach has been proposed for this purpose. One of the most important challenges of finding a comprehensive approach is the low efficiency of current predicting methods and the complexity of finding connections between uncertain predictions and decision variables (Georgakakos and Graham, 2008). However, the results of numerous studies have shown that simultaneous use of predicting water inflow into the reservoir and adaptive reservoir management can not only counteract the potential effects of climate change, but it also leads to a significant improvement of the efficiency of current reservoir operation methods (Yao and Georgakakos, 2001; Georgakakos and Graham, 2008; Raje and Mujumdar, 2010; Zhao et al., 2015).

Pishgah Hadian et al. (2016) investigated the trends of various climatic parameters such as runoff, precipitation, temperature, and evaporation for Sefidrud Dam reservoir located in northern Iran, in order to investigate the effects of climate change and emphasize on the updating operation policies of the Sefidrud Dam reservoir. The results showed decreasing trends for precipitation and minimum temperature and also increasing trend for maximum temperature. Therefore, predicting the water inflow values of Sefidrud River in the future is necessary for effective management and optimal operation of the Sefidrud Dam reservoir. The purpose of the current study is to investigate trends of water inflow into the Sefidrud Dam reservoir for the last decades. Prediction of water inflow into the Sefidrud Dam reservoir using dynamic neural networks for the coming years is another objective of this study. The parametric regression and non-parametric Mann-Kendall tests with the assumptions of independence, short-term and long-term persistence are used to determine trends. The homogeneity of the data used is studied using the statistical tests such as cumulative deviations, Worsley's Likelihood Ratio Test, and Bayesian inference. Two dynamic ANN models of NAR and NARX will be used to predict water inflow into the reservoir.

2. Case Study

The Sefidrud Dam basin is a subset of the Caspian Sea drainage area in the hydrological divisions of Iran. This basin is located in the north of Iran between latitudes of 34°,54' to 37°,56' north and longitudes of 46°, 31' to 51°,40' east. Covering about 9% of Iran's total area, it is one of the largest basins in Iran, limited to Alborz mountain range in the north and Zagros Mountain in the west. It supplies water demands of several provinces of the country, including Hamedan, Kurdistan, Zanjan, East Azerbaijan, Qazvin, Alborz and Gilan provinces. The climate condition of the Sefidrud basin is generally cold and semi-humid except the areas in the vicinity of the reservoir, which is mostly moderate and humid and without vegetation in most parts (Gilan Regional Water Authority, 2010). Annual rainfall of this area varies from 250 mm around the dam reservoir to 600 mm in the mountains of Taron, Kurdistan, and Azerbaijan (Dodangeh et al., 2012) with an average value of 415 mm (Hajiabadi and Zarghami, 2013). Figure (1) shows the location of the Sefidrud Basin.

Sefidrud River is formed by two tributaries named Kizil-Ozan and Shahrud rivers joining before Sefidrud Dam. Considering the location of the dam, Sefidrud Dam basin can be divided into two sub-basins of Kizil-Ozan and Shahrud with areas of approximately 49,500 and 5000 km², respectively (Gilan Regional Water Authority, 2010). Kizil-Ozan and Shahrud rivers originate from Kurdistan province in western Iran and the southern slopes of Alborz mountain range in northern Iran, respectively, and flow into the Sefidrud dam reservoir at distances of 800 km and 180 km, respectively. Flow discharge of both rivers depends on the snowmelt and spring floods (Hajiabadi and Zarghami, 2013).

Construction of Sefidrud dam at the junction of the two rivers began in 1955 and the operation process was started in 1961 with an initial reservoir storage volume of 1760 million cubic meters (MCM). This concrete weight dam is located in the north of Iran, about 200 km northwest of Tehran and 100 km south of the Caspian Sea, at latitude 32°, 73' north and longitude 50°, 74' east. Although it was generally constructed to supply the water demand of the agricultural sector of Gilan province, however, it was also used to produce 87.5 MW of hydropower energy, flood control, and supply the water demand for drinking and industrial activities of surrounding cities. With constructing this dam, the agricultural area in Gilan province increased from 90,000 hectares to 245,000 hectares and water demand in this part being largely supplied by this dam (Hajiabadi and Zarghami, 2013).

In this research, data of the flow discharge of Kizil-Ozan and Shahrud rivers are provided by Gilvan hydrometric station located 25 km upstream of the dam at about 320 meter above sea level, and Loshan hydrometric station, located 13 km from the Sefidrud dam and at about 300 meter above sea level. The long-term averages of flow discharge of these two rivers are 96.8 and 29.7 m³/s, respectively.

In this study the average monthly river flow of both hydrometric stations are used from 1967 to 2013 (47 years). River flow discharges have been extremely decreased in recent years with 60% of total discharge flowing into the dam reservoir in spring leading to many

problems for supplying water demands. The monthly flows of Kizil-Ozan and Shahroud rivers over the 47-year observation period are presented in figures (2) and (3), respectively.

3. Methodology

In this paper, statistical tests used to evaluate water discharge trends are divided into two categories: parametric and non-parametric tests. In addition, dynamic ANNs are used to predict water discharge of both tributaries of the Sefidrud River. These methods are briefly explained in the following subsections.

3.1. Trend tests

In general, statistical tests are divided into two categories of parametric and non-parametric tests. Non-parametric tests are superior to parametric ones because no information on the probability distribution of the underlying process is required (Ashraf Vaeqi et al., 2009). Most common parametric and non-parametric tests used for trend studies are Regression and Mann-Kendall tests, respectively.

3.1.1. Regression Test

All parametric methods are based on defining a regression relationship between the variable time series and the time parameter. In addition, according to the presumptions of all these methods, a probability distribution should be assumed for the time series. To obtain reliable results from parametric methods, the validity of this assumption should be evaluated. Also, constant variance of data and independency of observations are the most important assumptions of the parametric regression methods. The first step to examine trend of time series using the regression test is considering a linear relationship between the variable under study and time (Gharakhani and Ghahraman, 2010):

$$y = at + b$$

1

Where, y is the observed variable, t is time, and a and b are regression coefficients. Generally, Regression test statistic (T) with $n-2$ degrees of freedom is defined as follows:

$$T = \frac{b}{\sqrt{\frac{MSE}{S_{xx}}}}$$

2

Where, MSE is the mean squared error which is defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2$$

3

Where, y_i is the estimated value using regression method, x_i is the observed value, and n is the number of data points. Here, S_{xx} is also defined as follows:

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2$$

4

Where, $\bar{x}$ is the mean of observed data. In this method, the values obtained for the T statistic are compared with the critical values of the t-student test at the significance levels of 10, 5 and 1% (Table 1).

Table 1
Critical values of different test-statistics at 10, 5, and 1%significance levels

Test-statistic	Significance level of 10%	Significance level of 5%	Significance level of 1%
Cumulative Deviations- $\frac{Q}{\sqrt{n}}$	1.14	1.27	1.52
Cumulative Deviations- $\frac{R}{\sqrt{n}}$	1.44	1.55	1.78
Worsley	2.87	3.16	3.79
Bayesian	0.342	0.452	0.718
Mann-Kendall	1.64	1.96	2.57
Regression	1.89	2.92	6.97

3.1.2. Mann-Kendall Test

The Mann-Kendall test was first proposed by Mann (1945) and then developed by Kendall in (1948). This test has been widely used in various fields of research including study of trends for hydrological and climate time series (Azizi and Roushani, 2008; Sabziparvar and Shadmani, 2011). The S statistic of the Mann-Kendall test is defined as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

5

Where, x_i and x_j are data values in years i and j , respectively and n is the number of data. In addition, sgn is the sign function which is defined as follows:

$$\text{sgn}(x_j - x_i) = \begin{cases} 1 & x_j - x_i > 0 \\ -1 & x_j - x_i < 0 \\ 0 & x_j - x_i = 0 \end{cases} \quad (6)$$

The statistical distribution of S statistic for large number of n can be approximated using the normal distribution with mean value zero and standard deviation σ_s . The σ_s can be determined as follows (Ehsanzadeh and Adamowski, 2010):

$$\sigma_s = \sqrt{\frac{n(n-1)(2n+5)}{18}}$$

7

In addition, the normalized standard statistic for S statistic parameter (Z_s) can be determined using the following equation (Ehsanzadeh and Adamowski, 2010):

$$Z_s = \begin{cases} \frac{S-1}{\sigma_s} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sigma_s} & S < 0 \end{cases} \quad (8)$$

One of the limitations of Mann-Kendall test is that the results of the test for time series with periodic and seasonal fluctuations are not reliable (Ehsanzadeh and Adamovski, 2010). In order to overcome this limitation, the Mann-Kendall trend test is used for each month separately and then for the seasonal and annual average of the variables. If there is serial correlation among the time series of the studied variable, the assumption of data independence is unacceptable and some modifications should be applied to the standard Mann-Kendall

test. Therefore, when auto-correlation or short-term persistence (STP) exists, the statistical tests should be modified. Auto-correlation can reduce the significance of the obtained results, so the modified tests lead to stricter results about the significance analysis of trends. Long-term persistence (LTP), on the other hand, is another factor that affects the statistical significance of trends estimated in the time series. This type of persistence shows the long-term natural memory of a system. In fact, the long-term persistence of a phenomenon indicates to what degree the observation period of a variable is sufficient to be used for a trend detection analysis. Since serial dependence and Hurst phenomenon have been observed frequently in most hydrological and climate time series, it is preferred to examine the existence of short-term and long-term persistence when studying trends in time series. Therefore, modified forms of Mann-Kendall test are proposed which are explained in the following subsections.

3.1.2.1. Modified Mann-Kendall test with the assumption of short-term persistence (STP)

As mentioned before, one of the limitations of the classical Mann-Kendall test is the assumption of data independence and lack of storage capacity (Ehsanzadeh and Adamowski, 2010). If the time series are characterized with autocorrelation, some modifications to the statistical tests are required. Since serial dependencies are present in most hydrological and climate time series, the Mann-Kendall Test should be modified to account for this effect. Therefore, the normalized standard statistic (Z_s) of the Mann-Kendall test is modified using the following equation (Ehsanzadeh and Adamowski, 2010):

$$Z_s^* = \frac{Z_s}{\sqrt{\varphi_s}}$$

9

Where, Z_s^* is the normalized standard statistic modified for the STP assumption and φ_s is the serial dependence correction coefficient with one time lag, which is calculated as follows:

$$\varphi_s = 1 + 2 \frac{\rho_1^{n+1} - n\rho_1^2 + (n-1)\rho_1}{n(\rho_1 - 1)^2}$$

10

Where, ρ_1 is the serial correlation coefficient of one delay which is calculated as follows:

$$\rho = \frac{1}{n-1} \sum_{i=1}^{n-1} \frac{(x_i - \bar{x})(x_{i+1} - \bar{x})}{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

11

It is worth noting that, in this study, the effect of serial correlation is applied to Z only when the value of ρ_1 coefficient is greater than 0.1.

3.1.2.2. Modified Mann-Kendall test with the assumption of long-term persistence (LTP)

In 1956, Hurst observed a long-term serial correlation among time series which is known as Hurst phenomenon (Hurst, 1956). This phenomenon shows the correlation among time series for long-time lags and it can affect the reliability of the results of trend analysis (Fathian et al., 2014). The intensity of the Hurst phenomenon or long-term persistence (LTP) for time series is calculated using the Hurst exponent (H). A value of 0.5 for the Hurst exponent indicates that the data are randomly distributed. Values less than 0.5 indicate no long term persistence and, a Hurst exponent larger than 0.5 indicates the existence of long-term persistence. If the existence of this phenomenon is proven in time series, it is necessary to revise the results of the statistical tests.

Several methods have been proposed to calculate long-term storage capacity for time series. Among all, a common and simple method to calculate the Hurst coefficient is the (R/S) value, which is defined as follows (Fathian et al., 2014):

$$\left(\frac{R}{S}\right)_k = \frac{\text{Max}_{1 \leq t \leq k} (\sum_{i=1}^t x_i - \bar{x}) - \text{Min}_{1 \leq t \leq k} (\sum_{i=1}^t x_i - \bar{x})}{\sqrt{\frac{1}{k} \sum_{i=1}^k (x_i - \bar{x})^2}} \quad (12)$$

Where, R_k is the amplitude of the cumulative differences of the scaled standard deviation, S_k is the standard deviation of the time series, and other parameters are as defined previously. In this formula, k values range from zero to the number of data available. Hurst showed experimentally that when the values of (R/S) are plotted against time in an all-logarithmic diagram, the slope of the resulting line will be equal to the Hurst coefficient. By determining the slope of this line (H), the variance of the Mann-Kendall Test (σ_s) is modified as follows (Ehsanzadeh and Adamowski, 2010):

$$\sigma_s = \frac{n(n-1)(2n+5)}{18} \sqrt{\frac{n - \frac{1}{2}}{n - n^{2H-1}}}$$

13

Where, n is the number of data and H is the Hurst exponent. Having the new variance and using equation (8), the Z statistic value can be modified for the assumption of long-term persistence.

3.2. Homogeneity Tests

Heterogeneity of data is one of the main problems when studying trends of climate and hydrological time series. In most climate studies, the homogeneity of data is of considerable importance. However, it has been frequently seen in various studies that the climate data are heterogeneous (Buishand, 1982). Various factors can cause heterogeneity among climate time series including climate change (Alizadeh, 2001). Although it is not possible in most cases to find the main cause of heterogeneity of climate data (Buishand, 1982), however, if heterogeneity and significant trends exist simultaneously in time series of a basin, strong evidence have been provided to show the impact of climate change on the climate of the region. Therefore, the World Meteorological Organization (WMO) proposed the application of homogeneity tests in addition to trend analysis tests, to detect the climate change phenomenon (WMO, 1988). Data homogeneity tests have also been used in many similar researches in addition to analysis of trends (Ahmad et al., 2015; Modaresi et al., 2010). Different methods are used to study the homogeneity of climate data. In this research, the Cumulative Deviations Tests, Worsley's Likelihood Ratio Test, and Bayesian inference tests are used.

3.2.1. Cumulative Deviations Test

This test is based on the calculation of modified partial sums or cumulative deviations from the mean (S^*) (Buishand, 1982). Therefore, by assuming $S_0^* = 0$:

$$S_k^* = \sum_{i=1}^k x_i - \bar{x} \quad k = 1, 2, \dots, n$$

14

Where, x_i is the values examined at each time lag, $\bar{x}$ is the average of the time series, and n is the number of sample data. For homogeneous time series, S_k^* value should be close to zero. As S_k^* is a variable related to the average of the time series, dividing it by the standard deviation of the time series (D_x), will provide a more appropriate index to examine the homogeneity of the sample data (Buishand, 1982):

$$D_x = \sqrt{\sum_{i=1}^n \frac{(x_i - \bar{x})^2}{n}}$$

15

$$S_k^{**} = \sqrt{\frac{S_k^*}{D_x}} \quad k = 1, 2, \dots, n$$

16

Finally, Cumulative Deviation Test statistic(Q) can be calculated as follows:

$$Q = \max |S_k^{**}| \quad k = 1, 2, \dots, n$$

17

In addition, the statistic (R) can be used to calculate the homogeneity of data in this test (Buishand, 1982):

$$R = \max (S_k^{**}) - \min (S_k^{**})$$

18

3.2.2. Worsley's Likelihood Ratio Test

Worsley proposed another method for calculating data homogeneity. For this purpose, Worsley defined the value of Z_k^* as follows (Worsley, 1979):

$$Z_k^* = \frac{1}{\sqrt{k(n-k)}} S_k^* \quad k = 1, 2, \dots, n$$

19

In this method, the values of S_k^* are weighted so that most of the weight is allocated to the first and the last observation (S_1^* and S_n^*), and the closer to the mean data, the less weight is allocated to it.

Finally, the Worsley's test statistic (W) is calculated as follows (Buishand, 1982):

$$W = \frac{\sqrt{n-2} V}{\sqrt{1-V^2}}$$

20

$$V = \max_{1 \leq k \leq n-1} |Z_k^{**}|$$

21

Where, Z_k^{**} is the modified partial sum obtained by dividing Z_k^* by the standard deviation of the sample data (Buishand, 1982).

3.2.3. Bayesian inference

In order to identify changes in the mean of data, this test was proposed by Chernoff and Zachs (1963) and Gardner (1969). Assuming integrated distribution of data, Bayesian test statistics (U and A) are calculated as follows (Buishand, 1982):

$$U = \frac{1}{n(n+1)} \sum_{k=1}^{n-1} (S_k^{**})^2$$

22

$$A = \sum_{k=1}^{n-1} (Z_k^{**})^2$$

23

Where all parameters are defined previously. For all of these statistics, larger values represent the occurrence of gradual or sudden changes in data and lack of homogeneity among them.

Critical values for statistics of the mentioned tests, at different significance levels, were presented in Table (1). The values calculated for climate trends are significant only if they are higher than the critical values provided. In this table, the results of Regression test Statistic for two degrees of freedom, statistics of Cumulative Deviations Test, Worsley's Likelihood Ratio Test, and Bayesian inference are presented.

3.3. Dynamic artificial neural networks

In general, ANN models have been used to simulate the function of the human nervous system and cells. In this regard, Hebb (1949) tried to implement the structure and function of a real neural cell in a computing system leading to the basic idea of the ANN model. In general, ANN models are divided into two categories: static and dynamic or recursive networks (Gómez-Ramos and Vargas-Martinez, 2013). The main characteristic of static networks is the forward communication of neurons during network training process. In this type of network, there is no connection among the neurons of a layer with each other or the previous layer neurons. Multilayer Perceptron Neural Network and Radial Neural Networks are some types of static networks. However, in contrast to static networks, the main feature of dynamic networks is the dynamic and extensive communication among neurons of different layers. Partially Recurrent Neural Networks (PRN) and Auto-Regressive Neural Networks (ARN) are two types of dynamic networks. So far, several studies have compared the performance of static and dynamic neural networks, most of which indicated better performance of dynamic models for time series prediction problems (Kiani and Kastens, 2008). Among the various types of dynamic neural networks such as Nonlinear Auto-Regressive Neural Networks (NAR) and Nonlinear Auto-Regressive Neural Networks with exogenous inputs (NARX) have led to more acceptable results in various fields of research including analysis of nonlinear control systems and time series predictions (Beale et al., 2014). Therefore, in this study, NAR and NARX models are used to predict inflow time series for a specific time step in the future. These networks are briefly explained in the following sections.

3.3.1. Nonlinear Auto-Regressive Neural Network (NAR)

The NAR dynamic neural network is one of the simplest and most powerful structures used for predicting time series (Benmouiza and Cheknane, 2013). Unlike other common ANN models in which data are divided into two categories of input and target data and input data are used to train the target data, in NAR models only one series of data (as both input and output) is applied to the model. The unique structure of the NAR model allows all data to be applied to the network as a single interconnected data set. Similar to other dynamic neural network models, in the NAR model the output data set (same as input data set in this model) is used with a specific time lag for training processes. In these models, the values of the time series are predicted only using their previous values. The general equation for NAR model is as follows:

$$y(t+1) = f\{y(t), y(t-1), \dots, y(t-d)\}$$

24

Where, f is a nonlinear function, y is the time series, and d is the number of time lags which determines how much previous data are used for network training at each step. The network inputs are the observed values of the time series with a specific time lag. The NAR model is a memory-based ANN network like other dynamic networks. This means that in this network the amount of output data at any given time depends on not only the corresponding amount of input data but also the network memory of several previous input data sets. Therefore, this network is a powerful model for learning time sequence patterns (Beale et al., 2014). By properly selecting the number of neurons for the hidden layer and also time lags, the NAR model is a capable model for predicting the complex and nonlinear time series accurately (Benmouiza and Cheknane, 2013; Pawlus et al., 2013).

3.3.2. Nonlinear Auto-Regressive Neural Network with Exogenous Output (NARX)

The NARX model is a type of recurrent neural networks in which all layers are interconnected using complex feedback relations. The main idea of these networks is derived from linear Auto-Regressive Neural Networks with exogenous output, which have been widely used for time series prediction (Bierkens et al., 2001). The general equation governing the NARX model is as follows:

$$y(t+1) = f\{y(t), y(t-1), \dots, y(t-d_y), x(t), x(t-1), \dots, x(t-d_x)\}$$

25

Where, f is a nonlinear function, x is the input data set, y is the target (output) data set, dx is time lag of the input dataset, and dy is the time lag of the output data set. In this model, the value of the output for the time step t is calculated using the previous output and input values up to a specified time lag. In NARX, the network output values can be considered as estimates of the dynamic and nonlinear output values of the studied system. Therefore, at each stage of network training process, the output data set is used as new system input dataset to train new output values. So far, the NARX model has been used for various problems such as prediction of time series, filtering of nonlinear functions, and modeling nonlinear systems (Beale et al., 2014).

4. Results And Discussion

In this research, first, a trend analysis is performed on the discharge of both tributaries of Sefidruod River namely Gilevan and Loshan rivers for a 47-year statistical time period. It is worth noting that Pishgah Hadian et al. (2016) investigated the trend of hydrological data for this area, using different methods. However, here only the discharge time series are analyzed for trends for the purpose of updating the operation policies of the Sefidroud dam reservoir under uncertain future conditions. Then, according to the obtained results, future discharges of these rivers are predicted using dynamic NAR and NARX models. In order to validate and evaluate the obtained results both root mean square error (RMSE) and coefficient of determination (R^2) indices are used:

$$RMSE = \sqrt{\sum_{t=1}^n \frac{(y_t - y_0)^2}{n}}$$

26

$$R^2 = 1 - \frac{\sum_{t=1}^n (y_t - y_0)^2}{\sum_{t=1}^n (y_t - y_{bar})^2}$$

27

Where, n is the number of available data, and y_t , y_0 , and y_{bar} are the observed, predicted, and average values of the time series, respectively.

4.1. Trend analysis

Results of trend analysis for monthly inflow into the dam reservoir are presented in table (2). In this table, the results of Mann-Kendall (Z) and Regression (T) tests for water inflow and for each month of the year under three assumptions of independence, short-term, and long-term persistence are presented for both Gilevan and Loshan stations. Results of seasonal and annual average water inflow trend analysis of these stations are presented in table (3). It is worth noting that in the following tables, correction for short-term and long-term persistence has been applied only if autocorrelation coefficient above 0.1 and Hurst component above 0.65 have been observed.

Table 2
Results of Regression and Mann-Kendall tests for monthly water discharges

Variable (Station)	Statistic	Time Period											
		Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
Discharge(Gilevan)	Z	-4.40	-3.59	-3.54	-3.79	-2.89	-3.37	-3.54	-3.34	-3.92	-3.39	-3.56	-4.26
	Z _{STP}	-3.13	-2.21	-1.96	-2.44	-1.85	-2.97	-	-2.89	-3.11	-3.06	-	-3.40
	Z _{LTP}	-4.19	-	-3.33	-3.68	-2.73	-	-3.40	-3.13	-3.74	-3.23	-3.44	-3.97
	T	-2.30	-4.80	-4.70	-6.49	-6.36	-26.2	-63.10	-51.90	-36.1	-6.15	-1.59	-2.52
Discharge(Loshan)	Z	-3.07	-1.52	-2.19	-2.58	-2.38	-3.04	-3.00	-2.57	-4.33	-3.99	-4.70	-3.52
	Z _{STP}	-	-1.24	-1.75	-2.10	-2.05	-2.35	-2.69	-	-3.87	-3.55	-3.57	-2.56
	Z _{LTP}	-2.95	-	-2.10	-2.48	-2.28	-2.92	-2.89	-	-4.21	-3.88	-4.37	-3.05
	T	-0.68	-0.75	-0.97	-0.95	-1.02	-3.09	-7.95	-10.41	-9.56	-4.25	-1.50	-0.85

Table 3
Results of Regression and Mann-Kendall tests for seasonal and annual inflow

Variable-(Station)	Statistic	Time Period				
		Fall	Winter	Spring	Summer	Annual
Water inflow-(Gilevan)	Z	3.63	-3.52	-3.87	-3.85	-4.35
	Z _{STP}	-2.01	-2.66	-3.33	-3.38	-3.19
	Z _{LTP}	-3.45	-3.42	-3.64	-3.63	-4.08
	T	-3.00	-13.14	-47.11	-3.06	-18.02
Water inflow-(Loshan)	Z	-2.64	-2.99	-3.41	-4.27	-2.82
	Z _{STP}	-2.01	-2.29	-	-3.58	-
	Z _{LTP}	-	-2.78	-	-4.10	-
	T	-0.91	-2.10	-12.73	-3.11	-3.38

Results of analyzing trends in different months show significantly decreasing trends for discharge over the statistical period in both tributaries of Sefidrud River. Tables (2) and (3) show that almost all trends of Gilevan station are decreasing and significant at a significance level of 1%. In addition, in this station the effect of STP in December, January and February is more noticeable. Moreover, the results of Regression tests are similar to Mann-Kendall test in most cases, with the more obvious decreasing trends in spring based on this test. This observed downward trend in spring is extremely important since more than 60% of the total inflow into the dam reservoir flows in the spring. In Loshan station, the trends of monthly water inflow are decreasing at a significance level of 1% according to the results of Mann-Kendall test, except in November, December and February. Furthermore, the effect of autocorrelation coefficient and Hurst index for water inflow in this station is less than that of Gilevan station. In addition, the results of Regression test do not show a significant trend for most months in this station. Nonetheless, Table (3) shows a significant decreasing trend of the river flow discharge at the significance level of 1% for April, May, June, and July. Although the Regression test does not detect downward significant trends for discharges of Loshan station in most seasons of the year and also for the annual period, results of table (3) shows that discharge time series have significant downward trend in spring at the significance level of 1%. It should be noted that in most cases the results of Mann-Kendall test are in agreement with those of Regression test. However, due to the independency of the Mann-Kendall test from the mean and the underlying distribution of the sample data, and the ability to exert persistence effects, the results of the Mann-Kendall test are more reliable and accurate than other methods.

Decreasing of ground water levels and limitations of supplying water demands of different sectors lead to inflow reduction of Sefidroud basin (Mirabbasi Najafabadi and Dinpashoh, 2010). It should be noted that due to the increasing water demand and consequently uncontrolled increasing upstream water abstraction, the inflow into the Sefidroud dam reservoir has decreased dramatically. A number of

studies have pointed out that developing different upstream projects along with possible climate change will lead to a reduction of more than 40% of inflow into the dam reservoir in the future (Zarezadeh et al., 2012). Therefore, by adopting a comprehensive approach, these impacts should be evaluated in order to reduce damage and water scarcity in downstream areas of the basin. On the other hand, decreasing trends of precipitation in Sefidroud Dam basin have a significant effect on reduction of water inflow into Sefidroud dam (Dodangeh et al. 2012, Pishgah Hadian et al., 2016). It is worth noting that most of studies investigating the impact of climate change on river flow for snowy areas indicate a relative increase of river flow in winter, due to the relative increase in temperature and the earlier occurrence of snowmelt. The lower intensity of decreasing trends observed for water inflow in winter compared to spring in this study can be justified based on mentioned findings (Arnell and Reynard, 1996; Middelkoop et al., 2001; Ehsanzadeh and Adamowski, 2010). The occurrence of these changes highlights the importance of investigating these changes for planning and management purposes and modification of reservoir operation policies of this basin.

Table (4) presents a summary of results obtained from the classical Mann-Kendall test. In this table, the numbers 1, 2, and 3 indicate the significance levels of 10, 5, and 1%, respectively. Also, the negative or positive numbers determine if a downward or upward trend is observed. According to this table, 100% and 82% of the studied variables (monthly, seasonal, and annual data) have a decreasing trend at a significance level of 1% for Gilvan and Loshan stations, respectively.

Table 4
Trend analysis results for discharge based on Mann-Kendall test under independence assumption.

Time Period	Inflow		Time Period	Inflow	
	Gilevan	Loshan		Gilevan	Loshan
October	-3	-3	Fall	-3	-3
November	-3	+1	Winter	-3	-3
December	-3	-2	Spring	-3	-3
January	-3	-3	Summer	-3	-3
February	-3	-3	Annual	-3	-3
March	-3	-3			
April	-3	-3			
May	-3	-3			
June	-3	-3			
July	-3	-3			
August	-3	-3			
September	-3	-3			

Trend analysis considering short-term and long-term persistence for Gilevan and Loshan stations are also investigated. It should be noted that the values of critical test statistics at the significance levels of 1, 5, and 10% are 2.33, 1.65 and 1.28, respectively. The results show that, except some cold months of the year and only with the assumption of short-term persistence, the Gilevan River water discharge with the assumptions of independence short-term and long-term persistence has a significant decreasing trend at the significance level of 1%. The results obtained for Loshan station are somewhat similar to those of Gilevan station, with the difference that the decreasing trends observed under different assumptions are more consistent and the decreasing trends observed in the first half of the year are more statistically significant.

4.2. Results of homogeneity tests

Table (5) shows the results obtained from the data homogeneity tests. The results of table (5) show that, at the significance level of 10%, inflow data are heterogeneous in monthly scale in Gilvan station except in August, and in Loshan station except in November and December based on all tests.

Table 5
Results of homogeneity tests for monthly inflow data

Variable (Station)	Statistic	Time Period											
		Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.
Inflow (Gilevan)	Q	1.94	1.82	1.74	1.67	1.74	1.20	1.69	1.75	1.66	1.62	1.46	1.69
	R	1.86	1.87	1.86	1.79	1.94	1.29	1.79	1.67	1.61	1.66	1.52	1.77
	W	4.86	4.63	4.27	4.02	4.34	3.35	4.18	4.22	3.90	3.86	1.46	4.01
	U	1.35	0.88	0.64	0.65	0.76	0.62	1.14	1.00	1.12	0.90	0.64	1.03
	A	6.84	4.64	3.46	3.49	4.09	3.61	5.95	5.47	6.11	4.89	3.68	5.51
Inflow (Loshan)	Q	1.40	0.96	1.19	1.51	1.38	1.38	1.53	1.18	1.35	1.17	1.51	1.66
	R	1.45	1.12	1.31	1.64	1.56	1.49	1.70	1.19	1.35	1.17	1.49	1.65
	W	3.99	2.49	2.6	3.42	3.06	2.96	3.52	3.67	4.62	4.45	5.05	5.25
	U	0.92	0.19	0.22	0.45	0.52	0.70	0.93	0.60	1.02	0.79	1.24	1.16
	A	5.06	1.13	1.16	2.38	2.64	3.77	4.78	3.46	5.63	4.64	7.06	6.57

Comparing the results of the homogeneity tests confirm the heterogeneity of inflow data in the monthly scale. The results of homogeneity tests for monthly inflow are in agreement with those of trend analysis results. Reviewing the literature of similar studies show that in most cases, there is a correlation between the results of homogeneity tests and the trend test results (Modaresi et al., 2010). In other words, higher significance level of heterogeneity test results leads to the higher significance level of trend test results. Therefore, more reliable results can be obtained if trend and homogeneity tests are used simultaneously to examine variations in climatic variables.

4.3. Inflow prediction under future conditions using dynamic ANN models

Considering the results obtained from trend analysis of the observed inflow variables, it seems necessary to predict river discharges under future conditions. For this purpose, first, discharge values are simulated using dynamic NAR and NARX models, and the obtained results are compared with the actual water discharge values for the last 5 years of the observational data. Then, water discharge values for both river tributaries are predicted for the next 5 years in future using the unique characteristics of dynamic ANN models.

In this study, a NAR model in which previously observed discharge data, precipitation data and time index (T) are used for simulation and a NARX model in which only precipitation data are used as input data both proposed by Pishgah et al. (2020) are employed for simulating the last 5 years of the inflow data and also to predict discharge values for the following 5 years in the future. For these models, 12 time lags are defined for both input and output data sets. Comparison of the results of simulation process for last 5 years of the observational data shows that the obtained RMSE and R^2 values of the proposed NAR model are 87.72 m³/s and 0.528 for the Kizil-Ozan River and 21.52 m³/s and 0.712 for the Shahroud River, respectively. In addition, the RMSE and R^2 values of the proposed NARX model are 133.87 m³/s and 0.1 for the Kizil-Ozan River and 23.71 m³/s and 0.65 for the Shahroud River, respectively. The obtained results show that the results of dynamic NARX model are not as acceptable as those of the NAR model, which could be due to the more complexity of this model and the inadequacy of the input data.

Figures (4) and (5) compare inflow values simulated by dynamic NAR and NARX models (months 1 to 60) with observed values for the last 5 years of the study period for the Kizil-Ozan and Shahroud Rivers, respectively. These figure also shows predicted values using the dynamic ANN models for these rivers for the following 5 years in the future (months 61 to 120).

Comparison of the results shows that the error values of water flow simulation using dynamic NAR network model is less than those of NARX model. In addition, the water flow values predicted using the NAR model for the next 5 years are much lower than those of NARX model. Furthermore, the predicted water flow values of both rivers obtained using both models are zero in many months of the year, implying a significant decline in water flow patterns for the following years in both rivers.

It is necessary to pay attention to the fact that the predicted values for the next 5 years are not perfect and have some defects. High difference between minimum and maximum discharge values predicted by NARX model for Kizil-Ozan River and NAR model for Shahroud River are among the mentioned defects. In addition, high fluctuations of discharge values predicted by NAR model are noticeable for Shahroud River. Here, the best predicted discharges are selected using the Closed Loop Mean Squared Error (CMSE) criterion, which is a

nonlinear index for studying the error of values predicted by dynamic ANN models. The best model for predicting inflow into the reservoir is the one which minimizes the mentioned index. However, engineering judgment may also be used to select the best water discharge prediction model.

Finally, inflows predicted using NAR and NARX models are analyzed for trends using trend analysis tests. Tables (6) and (7) show the obtained results for inflows into the dam reservoir over the statistical period and the water inflow predicted using different models for Kizil-Ozan and Shahroud Rivers, respectively.

Table 6
Comparison of the observed and predicted water discharge trends for the Kizil-Ozan River using all proposed tests

Test Time period	Mann-Kendall Statistic (Z)	Mann-Kendall Statistic with the assumption of STP (Z_{STP})	Mann-Kendall Statistic with the assumption of LTP (Z_{LTP})	Regression Statistic (T)
47-year statistical time period	-4.35	-3.19	-4.08	-18
Last 10 years of the statistical time period	-1.43	-1.43	-1.33	-3.45
Next 5-year prediction (NAR model)	-1.71	-1.60	-1.51	-3.99
Next 5-year prediction (NARX model)	-2.20	-1.71	1.94	18.58

Table 7
Comparison of the observed and predicted water discharge trends for the Shahroud River using all proposed tests

Test Time period	Mann-Kendall Statistic (Z)	Mann-Kendall Statistic with the assumption of STP (Z_{STP})	Mann-Kendall Statistic with the assumption of LTP (Z_{LTP})	Regression Statistic (T)
47-year statistical time period	-2.82	-2.76	-2.79	-3.38
Last 10 years of the statistical time period	-1.43	-1.59	-1.33	-1.22
Next 5-year prediction (NAR model)	-2.20	-1.89	-1.78	-2.50
Next 5-year prediction (NARX model)	-1.71	-1.47	-0.74	-1.14

Comparison of results shows that although water discharge is characterized with decreasing trend throughout the statistical period, the slope of these trends has decreased in the last 10 years, which may be due to the overall decreasing the average water discharge values for these years. This negative decreasing trend continues over the next 5-year water inflow predicted using dynamic NAR and NARX models, which indicates the relatively appropriate prediction by dynamic ANN models and also the importance of paying attention to this declining trend for dam reservoir planning and management for the future condition.

5. Concluding Remarks

In this research, the efficiency of dynamic NAR and NARX models for predicting inflow into the Sefidrud dam reservoir, as a real case study, was investigated using parametric and non-parametric statistical tests. At first, water discharge trends of Kizil-Ozan and Shahroud rivers, as tributaries of Sefidrud River, over a 47-year statistical period were determined using parametric Regression and non-parametric Mann-Kendall tests with the assumptions of independence, short-term and long-term persistence. Then, the homogeneity of the data was investigated using the statistical tests of Cumulative Deviations, Worsley's Likelihood Ratio, and Bayesian inference. The results of trend analysis tests for water discharge in various months during the 47-year statistical period indicate a significant decreasing trend for this variable over the statistical period for both rivers. Considering significant trends for water inflow into the dam reservoir, it is necessary to use appropriate methods to predict water inflow into the dam reservoir for the future conditions. Therefore, inflow into the Sefidrud dam reservoir from Kizil-Ozan and Shahroud rivers were simulated using dynamic NAR and NARX models, and the obtained results were compared with the actual water inflow values for the last 5 years of the statistical period. Comparison of the results showed that the results obtained from the dynamic NARX model are not as acceptable as those of the NAR model. Finally, discharge values of both rivers

were predicted for the next 5 years at future using dynamic ANN models. The obtained results showed that water discharge values predicted for the next 5 years using the NAR model are far lower than those of NARX model for both rivers. Finally, in order to validate the predicted trends obtained from dynamic NAR and NARX models, parametric Regression and non-parametric Mann-Kendall tests were used. The results showed a continuous decreasing trend for the 5-year water inflow prediction using dynamic NAR and NARX models. The significant continuous decreasing trend for the water inflow values into the dam reservoir predicted by mentioned models, shows the necessity of paying attention to this issue in determining the operation rules of the Sefidrud dam reservoir.

Declarations

- **Conflict of Interest:**

All authors declare that he and she have no conflict of interest.

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- **Ethical approval:**

This article does not contain any studies with human participants or animals performed by any of the authors.

- **Data availability**

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

Figure 1

Location of Sefidrood Basin in the hydrological divisions of Iran

Figure 2

Monthly flow discharge of Kizil-Ozan River over 47-year time period

Figure 3

Monthly flow discharge of Shahrud River over 47-year time period

Figure 4

Actual and predicted water discharge values for Kizil-Ozan River

Figure 5

Actual and predicted water discharge values for Shahroud River