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A Comparative Assessment of Artificial Neural Network, Generalized Regression Neural Network, Least-Square Support Vector Regression, and K-Nearest Neighbor Regression for Monthly Streamflow Forecasting in Linear and Nonlinear Conditions

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Abstract Monthly forecasting of streamflow is of particular importance in water resources management especially in the provision of rule curves for dams. In this paper, the performance of four data-driven models with different structures including Artificial Neural Network (ANN), Generalized Regression Neural Network (GRNN), Least Square-Support Vector Regression (LS-SVR), and K-Nearest Neighbor Regression (KNN) are evaluated in order to forecast monthly inflow to *Karkheh* dam, Iran, in linear and non-linear conditions while the optimized values of the model parameters are determined in the same condition via the Leave-One-Out Cross Validation (LOOCV) method. Results show that the performance of the models is different in linear and nonlinear conditions; the cumulative ranking of the models according to the three assessment criteria including NSE, RMSE and R^2 indicates that ANN performs best in linear conditions while LS-SVR, GRNN and KNN are in the next ranks, respectively. But in nonlinear conditions, the best performance belongs to LS-SVR, followed by KNN, ANN, and GRNN models.

Keywords Comparative assessment · Cumulative ranking · Karkheh · Leave-One-Out Cross Validation (LOOCV) · Linear and Nonlinear conditions

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1 Introduction

One of the essential issues in water resources planning and management is the awareness of the inflow to the reservoir of dams. Therefore, the forecast of inflow to a dam is of particular importance in the operating decisions. Since rule curves of dams are usually in monthly time scales, the monthly forecasting of inflows to dams is essential.

In order to forecast monthly streamflows, several data-driven methods are proposed including: supervised training methods like various Neural Networks (NN) and Support Vector Machines (SVM), fuzzy methods, and nonparametric methods such as K- Nearest Neighbor (KNN) Regression. Among all these methods, the fuzzy method depends on the user expertise, while the efficiency of other methods depends on the ability of the model to discover the relationship between predictor and predicted variables. Moreover, each of the above mentioned models enjoys a special structure different from the others. However, the main concern is to select the most reliable and confident method via the comparative researches.

Some researches revealed that Generalized Regression Neural Network (GRNN) model excelled the types of Feed Forward Back Propagation (FFBP) and Multi Layer Perceptron (MLP) of Neural Network models, in order to monthly streamflow and drought forecasting (Hosseini and Araghinejad, 2015; Cigizoglu, 2005; Kişi, 2008). However, Fallah Haghgoo and Sharifi (2011) suggested that the performance of MLP is better than GRNN in monthly streamflow forecasting.

Moreover in several studies about annual and monthly streamflow forecasting, it was reported that Support Vector Machine (SVM) produced the most accurate results in comparison of models like Artificial Neural Network (ANN), Auto Regressive Moving Average (ARMA), and Multiple Linear Regression (MLR) (Lin et al., 2006; Wang et al., 2009; Kalra and Ahmad, 2012; Kalra et al., 2013, Callegari et al., 2015). On the other hand, Shrestha (2014) suggested that the patterns of annual forecasted streamflow by ANN and SVM, in four hydrological stations all over the Utah State, are similar. Besides, Bharti et al. (2017) indicated that ANN model outperforms the Least Square- Support Vector Regression (LS-SVR) model for prediction of monthly runoff while LS-SVR model surpasses ANN models for monthly sediment prediction.

The KNN model has been applied in fewer studies as compared to ANN and SVR models in order to forecast process; however, Wu and Chau (2010) revealed that the performance of KNN model is superior to ARMA and ANN model for monthly streamflow forecasting, whereas in the researches done by Wu et al. (2010) and Mekanik et al. (2013), it was concluded that the preference of ANN model was over KNN and MLR models, in monthly and seasonal rainfall forecasting.

As can be seen from the previous researches reported in the literature, the results obtained from these studies are inconsistent which can be because of the differences between study areas, data sets, and the selected structures for each of the models. On the other hand, the type of relationships between predictor and predicted variables, which can be linear or nonlinear, essentially affect the results of the models because of their various structures; yet, in the previous studies, the evaluation of the model performance has been done regardless of this point. Moreover, in the previous researches, the efficiency of the GRNN, KNN, and SVR models has been compared only with ANN model or ANN and MLR models, and in any of them, a comparative assessment of the performance of all the above models has not been done.

Therefore, in this paper, the efficiencies of the best forecasting models identified in the previous researches including two neural network models, i.e. ANN and GRNN models, as well as, LS-SVR and KNN models are compared in the equal conditions in terms of the study area, data sets, and the methods of determining the best structure of the models while they are assessed based on various linear and nonlinear patterns of forecasting between predictor and predicted variables. The models are evaluated in order to forecast the monthly inflow to the *Karkheh* reservoir, Iran, whilst all of them are applied with their best structure where the absolute optimum values of the effective parameters are determined with the same manner involving Leave-One-Out Cross Validation (LOOCV) method.

2 Case Study and Data

In this paper, the forecast of monthly inflow to *Karkheh* reservoir is investigated, as the case study. *Karkheh* dam is located on the *Karkheh* River in the southwest of Iran (Fig. 1). *Karkheh* River originates from two branches, namely, *Gamasiab* in the northeast and *Gharesu* in the northwest. The confluence of these two rivers forms *Seimareh* River at the end of *Kermanshah* plain. The joint of the two rivers, i.e. *Seimareh* and *Kashkan*, which originates from the east part of the basin, forms *Karkheh* River. The location of the branches of *Karkheh* River is showed in Fig. 1. *Karkheh* dam is one of the largest multi- purpose earthen embankment dams in the world, which was exploited on 2003 for agricultural water supply, flood control, and Hydropower protection. Therefore, the forecast of its inflow is of importance.

The upper basin of the *Karkheh* dam has different weather conditions such that its northern and eastern regions are mountainous area with cold winters and mild summers while the western and southern regions are plains and foothills with mild winters and long and warm summers. However, the climate of this basin is Mediterranean with the average annual precipitation of 300–800 mm. The pattern of 32-year average of monthly precipitation at the upper basin of *Karkheh* dam (from 1982 to 2013) together with the 32-year average of

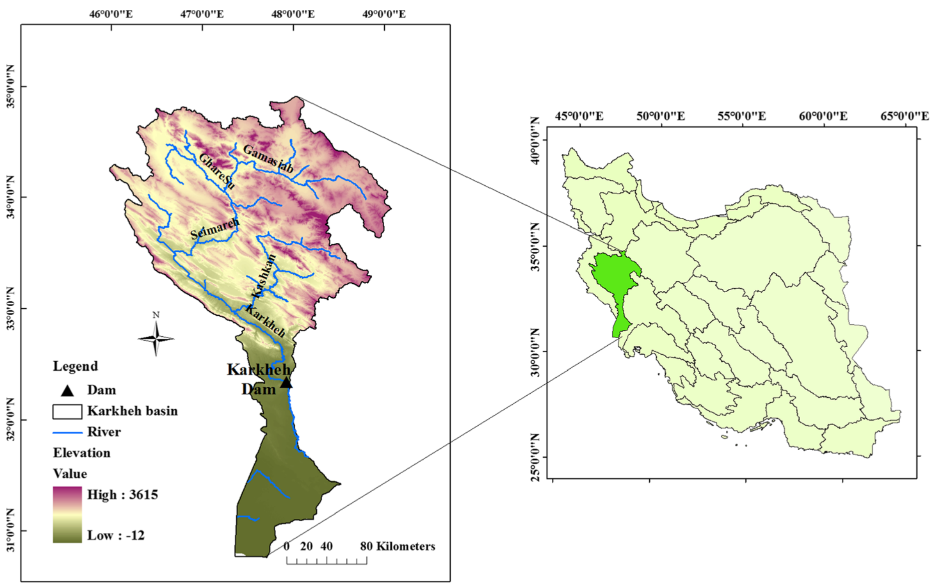

Fig. 1 The location of the *Karkheh* dam on the *Karkheh* River, Iran

monthly inflow to *Karkheh* reservoir in the same period of precipitation is illustrated in Fig. 2. As can be seen from Fig. 2, the main precipitation in the basin occurs From December to April while the main volume of inflow to *Karkheh* reservoir is from November to June which is greater than 100 MCM. Moreover, the patterns of the upper basin rainfall and the inflow to the reservoir are not completely consistent which is because of water harvesting along the river for agricultural purposes before the reservoir. It is noted that the data of inflow to *Karkheh* dam before 2003 (the year of *Karkheh* dam exploitation) have been derived from the information of the hydrometric station at the upstream of *Karkheh* dam.

The data applied in this study include: monthly inflow to *Karkheh* reservoir, monthly rainfall and monthly Snow Area Extent (SAE) at the upper basin of *Karkheh* dam over 32 water years (from October 1982 to September 2013). Snow area extent data are obtained from the images of MODIS/ TERRA satellites (MOD 10.A2). Based on the Pearson Correlation Coefficient (R) and Modified Mutual Information (MMI) indices, as presented in Modaresi et al. (2016), with the threshold of 0.5 and Forward Selection method (FS) (Chen et al., 1989), the best predictors for each month have been determined and presented in Table 1. With respect to Table 1, it can be said that due to the type of weather conditions in this basin, the type of predictors for some of months are different from other months; such that the streamflow of March and April can be forecasted in a better way by the use of the SAE of February because the main snowfalls occur in this basin in February. Further, since the autumn rainfalls in this basin begin in late October, the streamflow of November has the most dependency on the precipitation of October. The streamflows of April and June also depend on the rainfall of their previous month, while the streamflows of other months can be forecasted by the streamflow of their previous month.

3 Methodology

As mentioned before, in the current paper, the performances of four data-driven models including: two different neural networks, i.e. Artificial Neural Network (ANN) and Generalized Regression Neural Network (GRNN), as well as, Least Square- Support Vector Regression (LS-SVR), and a nonparametric regression method (K- Nearest Neighbor (KNN)) are evaluated in order to forecast monthly streamflow in linear and nonlinear conditions of relationship between predictor and predicted variables. Since the numbers of predictors are more than one in most of months, considering the amount of Pearson Correlation Coefficient

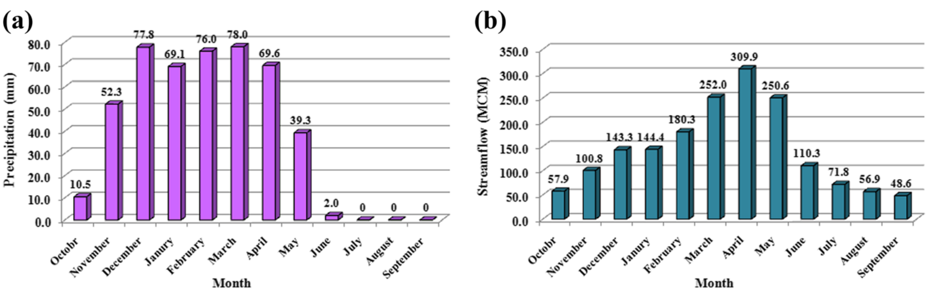

Fig. 2 The 32-year average of monthly precipitation of *Karkheh* basin (a) and monthly inflow to *Karkheh* dam (b) from 1982 to 2013

Table 1 The most appropriate predictors for monthly streamflow forecasting of *Karkheh* River, Iran

Predictors	Forecasted Variable: Monthly streamflow											
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Precipitation in October		√										
Precipitation in March							√					
Precipitation in May									√			
streamflow in September	√											
streamflow in November			√									
streamflow in December				√								
streamflow in January					√							
streamflow in March								√				
streamflow in April								√				
streamflow in May									√			
streamflow in June										√		
streamflow in July											√	√
streamflow in August												√
SAE* of February						√	√					

* SAE: Snow Area Extent

(R) alone can not specify the linear conditions between predictors and predicted variable. But in linear conditions with several predictors, Multiple Linear Regression model (MLR) performs best; therefore, in this study, the performance of MLR model is considered as the basis of determining linear and nonlinear conditions.

Also, to determine the absolute optimum amount of all parameters of the models, the *leave-one-out* cross validation method (LOOCV) has been applied. The brief descriptions of the mentioned methods are as follows: It is noted that in all models the matrix/vector of input and the vector of target data are including the observed data of predictors and predicted variables for each month which are $X_t = \{x_{1,t}, x_{2,t}, \ldots, x_{m,t}\}$ and T_t, $t = 1,2,\ldots,n$, respectively, where n is the number of data and m is the number of predictors.

3.1 Artificial Neural Network (ANN)

In this paper, a neural network with the structure of Multi Layer Perceptron (MLP) is applied where one middle layer is considered. In this type of neural network, the number of neurons in the input and output layers are equal to the number of predictors (m) and predicted variable (streamflow), respectively, while the number of the neurons in the middle layer is variable, the optimum value of which should be calculated.

The functions used in the neurons of the middle and output layer are of linear and sigmoid types, respectively, as presented in Eq. 1 and 2 (Araghinejad, 2014):

$$f(x) = x \tag{1}$$

$$f(x) = \frac{1}{1 + e^{-\alpha x}} \quad \alpha > 0 \tag{2}$$

To calculate the functions in each neuron, a weight (w) and bias (b) is considered for inputs of the neurons as $(w_j x_j + b_j)$ where $j = 1,2,\ldots,m$, the optimum values of which should be determined via calibration of the model.

In order to train or calibrate the neural network, a Feed Forward Back Propagation (FFBP) algorithm has been applied, to achieve the best forecasts, where the error function in Eq. 3 is minimized for each of iterations, known as epochs (Araghinejad, 2014):

$$E = \frac{1}{nc} \sum_{i=1}^{nc} e_i^2 \tag{3}$$

Where, E is the error function; e_i is the error of the model simulation for i^{th} training pair data and nc is the number of training pairs.

3.2 Generalized Regression Neural Network (GRNN)

GRNN is a type of neural networks based on radial basis function (RBF), where a probabilistic structure is applied for simulating the dependent variables in a regression function simulation problem. Because of having probabilistic structure, it does not face the problem of local minima which other neural networks encounter (Cigizoglu, 2005).

GRNN is a three layer neural network where the number of neurons in the input and output layers is equal to the dimension of input and output vectors, respectively, just like the artificial neural network. But, the number of the neurons in the middle layer, unlike the artificial neural network, is clear and equal to the number of observed data used for the model calibration (Araghinejad, 2014).

The function implemented in the middle layer of this neural network is a normal (Gaussian) performance function as follows:

$$\begin{aligned} f(X_r, t) &= e^{-[I(t)]^2} \\ I(t) &= \|X_r - X_t\| \times 0.8326/h \quad , \quad t = 1, 2, \ldots, n \end{aligned} \tag{4}$$

Where, $\|X_r - X_t\|$ is Euclidean distance function between real time vector of predictors (X_r) and the observed vector of predictors related to the t^{th} neuron (X_t), and h is the *spread* parameter that presents the spread of radial basis function and adjust the function to achieve the most appropriate fitness. The typical amount of *spread* usually equals 1.0 while its larger amounts result in the smoother function approximation and the smaller ones leads to closely fitness; however, its amount should be determined by the user in the range of ($h > 0$).

The output of this model (Y_r) (forecasted stremflow) for the vector of (X_r) is calculated based on a kernel function of the normal performance function outputs [$f(X_r,t)$] as follows:

$$Y_r = \frac{1}{\sum_{t=1}^{n} f(X_r, t)} \sum_{t=1}^{n} [f(X_r, t) \times T_t] \tag{5}$$

3.3 Least Square- Support Vector Regression (LS-SVR)

Least Square-Support Vector Regression (LS-SVR) is a type of SVR model, where the least square method is used for finding the hyper planes which have the maximum distance from the nearest observed data or support vectors in both sides.

The beneficial advantage of LS-SVR model over neural networks is to apply the principle of the structural risk minimization (SRM) to recognize the pattern between predictor and predicted variables while the empirical risk minimization (ERM) principle is performed in neural networks (Modaresi and Araghinejad, 2014).

In LS-SVR method, a nonlinear mapping of ϕ in the trait space for $X_t \in R^m$ as the input data and $Y(X_t) \in R$ as the output data is calculated as follows (Suykens et al., 2002):

$$Y(X_t) = w^T.\phi(X_t) + b \tag{6}$$

Where, w and b are the amount of weights and biases of the regression function, respectively, calculated via minimization of the following objective function:

$$\underset{w,b,e_i}{Min}\ j(w,e) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{t=1}^{n} e_t^2 \qquad S.t: T_t = w^T\phi(X_t) + b + e_t \quad t = 1, 2, \ldots, n \tag{7}$$

Where, e is the amount of the errors, and *Gamma* (γ) is the regularization parameter of the model that controls the flatness of approximation function, the optimum amount of which should be determined by the user. The small and large values of *Gamma* indicate the simple and complicated LS-SVR model (Suykens et al., 2002).

Solving the objective function by the use of Lagrange method based on Karush-Kuhn-Tucker condition results in the following equation:

$$Y(X) = \sum_{t=1}^{n} \alpha_t K(X, X_t) + b \tag{8}$$

Where, $K(X,X_t)$ is kernel function, having three types of linear, polynomial and radial basis function shown in Table 2, and α_t ($t = 1,2,\ldots,n$) are Lagrange multipliers or support values.

3.4 K-Nearest Neighbor Regression (KNN)

K-nearest neighbor (*K*-NN) regression is a nonparametric regression method, where the information derived from the observed data is applied to forecast the amount of predicted variable in real time without defining a predetermined parametric relation between predictor and predicted variables.

The basis of this method is on calculating the similarity (neighborhood) of the real time amount of predictors $X_r = \{x_{1r}, x_{2r}, x_{3r}, \ldots, x_{mr}\}$ (with unknown forecasted streamflow) with the amount of predictors for each of historical observations $X_t = \{x_{1t}, x_{2t}, x_{3t}, \ldots, x_{mt}\}$ via Euclidean distance function (D_{rt}) as follows (Araghinejad, 2014):

$$D_{rt} = \sqrt{\sum_{i=1}^{m} w_i (x_{ir} - x_{it})^2}\ , \quad t = 1, 2, \ldots, n \tag{9}$$

Table 2 The kernel functions of LS-SVR model

Kernel Name	Kernel Function
Linear	$K(x_i, x_j) = x_i^T x_j$
Polynomial	$K(x_i, x_j) = (x_i^T x_j + \tau)^d$
Radial Basis Function (RBF)	$K(x_i, x_j) = \exp(-\lVert x_i - x_j \rVert^2/\sigma^2)$

Where, w_i ($i = 1,2,\ldots,m$) are the weights of the predictors, summation of which is equal to one. The forecasted (estimated) streamflow (Y_r) is calculated using the following probabilistic function of the observed streamflows (T_j):

$$Y_r = \sum_{j=1}^{K} f\left(D_{rj}\right) \times T_j \tag{10}$$

Where, $f(D_{rj})$ is the kernel function of the K nearest neighbors (K observed data with the lowest distance from the real time predictor), calculated based on distance amounts (D_{rt}) as follows:

$$f\left(D_{rj}\right) = \frac{1/D_{rj}}{\sum_{j=1}^{K} 1/D_{rj}} \tag{11}$$

In K-nearest neighbor algorithm, the amount of predictor weights (w in equation 9) and number of neighbors (K) affect the final results; therefore, their optimum amounts should be calculated to achieve the most appropriate results.

3.5 Multiple Linear Regression (MLR)

In order to identify the linear conditions between predictor and predicted variables, multiple linear regression model, which is a parametric method, is used in this paper, presented as follows (Araghinejad, 2014):

$$Y_r = \beta_0 + \sum_{i=1}^{m} \beta_i x_{ir} \quad i = 1, 2, \ldots, m \tag{12}$$

Where, Y_r is the estimated (forecasted) variable (streamflow), $X_r = (x_{ir}, i = 1, 2,\ldots,m)$ is the real time vector of predictors and $\beta_i(i = 1, 2,\ldots, m)$ is coefficient of the predictors, the amounts of which are calculated using the least square error optimization based on observed data.

3.6 Leave-One-Out Cross-Validation method (LOOCV)

The Leave-one-out cross-validation (LOOCV) method is a special case of cross-validation where the number of folds equals the number of observed data. Thus, the learning algorithm is applied once for each instance, using all other instances as a training set and using the selected instance as a single-item test set (Sammut and Webb, 2010).

In this paper, in order to determine the optimum values of all input parameters of the models, the LOOCV method has been used based on all of the possible values for each parameter of the models using programming (coding) in MATLAB. In this method, the value produced the minimum average error in LOOCV process has been selected as the optimized value of each parameter.

The advantage of this method in comparison with the optimization algorithms, in order to find the optimum values of the parameters, is to examine all of the possible amount of the model parameters; Therefore, it can be sure that the optimum value resulted from this method is the absolute optimum value while those obtained from the optimization algorithms are not necessarily the best optimum value because they may be the local optimum values.

In Table 3, the name of all input parameters of each model whose optimum values for each month have been determined via the LOOCV method is presented.

3.7 Assessment Criteria

The performance criteria used in this study in order to assess the forecasting models are as follows (Nash and Sutcliff, 1970; Araghinejad, 2014):

- Nash- Sutcliff:

$$NSE = 1 - \frac{\sum_{t=1}^{n}(T_t - Y_t)^2}{\sum_{t=1}^{n}\left(T_t - \overline{T}\right)^2} \tag{13}$$

- Root Mean Square Error:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(T_t - Y_t)^2}{n}} \tag{14}$$

- Coefficient of Determination:

$$R^2 = \frac{\left[\sum_{t=1}^{n}\left(T_t - \overline{T}\right)\left(Y_t - \overline{Y}\right)\right]^2}{\sum_{t=1}^{n}\left(T_t - \overline{T}\right)^2 \cdot \sum_{t=1}^{n}\left(Y_t - \overline{Y}\right)^2} \tag{15}$$

Where, Y_t and T_t are forecasted (estimated) and observed values of streamflow, respectively for t^{th} data, $\overline{T}$and $\overline{Y}$are the average of observed and forecasted values of streamflow (forecasted variable) and n is the number of data.

NSE takes on values between -∞ to 1.0 for the worst and best model performance, respectively. The values between 0.0 and 1.0 indicates the acceptable level of performance while the values ≤0.0 reveals that the average of observed data is a better estimation than the forecasted values, which indicates unacceptable performance (Moriasi et al., 2007).

RMSE ranges from 0.0 to +∞ while the range of R^2 is between 0 and 1.0. The lower RMSE and higher R^2 indicate the more performable model.

Table 3 The optimized parameters of the forecasting models using LOOCV method

Model Name	Optimized Parameter(s)
Artificial Neural Network (ANN)	Initial weights and biases of neuron connections in different layers (*w* & *b*), Number of hidden layer neurons
Generalized Regression Neural Network (GRNN)	Spread parameter (*h*)
Least Square-Support Vector Regression (LS-SVR)	Kernel function type, Kernel Parameters, Regularization parameter (*Gamma*)
K-Nearest Neighbor Regression (KNN)	Weight of predictors (*w*), Number of nearest neighbors (*K*)
Multiple Linear Regression (MLR)	Predictor coefficient (β)

4 Results and Discussion

Based on the optimum value of the model parameters obtained from the LOOCV method for each month, all of the models have been trained using 22 data and tested (validated) using 10 remaining data.

Since the goal of modeling is to achieve the more accurate forecasts in validation phase the results of the four forecasting models in comparison with MLR model, as the basis of linearity, have been illustrated in Fig. 3 according to the three assessment criteria.

It can be seen from Fig. 3 that the relationship between predictor and predicted variables in January, February, July, and August is almost linear, because the accuracy of the results of MLR is high based on all three criteria while in other months the non linear relationship is more than linearity; this is particularly visible in the months of December, April, June, and September.

A general assessment of all the forecasting models reveals that a specific model could not produce the most accurate results in all months or conditions. However, comparing the results of the models in the condition of linearity and non linearity, it can be suggested that in linear conditions that the accuracy of MLR model is high, the accuracy of the results of KNN and GRNN models is lower than other models specially MLR. This condition is observable in Jan, Feb, Jul, Aug, and also Nov. On the contrary, in the conditions of nonlinearity, the accuracy of the results of KNN and GRNN is higher than MLR model. This is visible in Oct, Dec, March, Apr, May, Jun, and Sep.

Evaluation of the results of ANN and LS-SVR models indicates that these models have been produced the most accurate results in both conditions on linearity and nonlinearity in most of months; however, the accuracy of ANN results in linear conditions is higher while the efficiency of LS-SVR model in April, and September is obviously better than ANN and also two other models.

Moreover, comparison of the results of the two neural networks ANN and GRNN indicates that in most of months when the nonlinearity of relationship between predictor and predicted variables is more than linearity, like in Apr, May, Jun, and Sep, the performance of GRNN is better than ANN model; however, in most of linearity condition, like Feb, Mar, Jul, and Aug, ANN is more efficient than GRNN model.

In order to evaluate the efficiency of the models, their performances are assessed according to the performance ratings developed by Moriasi et al. (2007) for NSE and RMSE indices (Table 4), and by Diaz-Ramirez et al. (2011) for coefficient of determination (R^2) (Table 5) for streamflow forecasting in monthly time steps. The Tables 4 and 5 show the number of the results in each class of performance for each model.

With respect to Table 4, it can be said that the performance of LS-SVR model is better than other models based on NSE and RMSE, because only in 2 months its results were placed in the range of "Unsatisfactory", while the results of ANN and KNN in 5 months and the results of GRNN in 6 months were placed in this rate of performance. Moreover, the performance of LS-SVR was "Very good" and "Good" in 5 months; in this respect, ANN model is the second better model with 4 months whereas GRNN and KNN are in the next ranks, respectively. Besides, the performance of MLR in 3 months, i.e. Jan, Feb, Aug, is in the range of "Very good" and in July is in the range of "Satisfactory", which confirms linear condition in these months and non linearity in other months.

Nevertheless, as can be seen from Table 5, the performance rating of the models based on R^2 is somewhat different from that of NSE and RMSE; such that the performance of GRNN

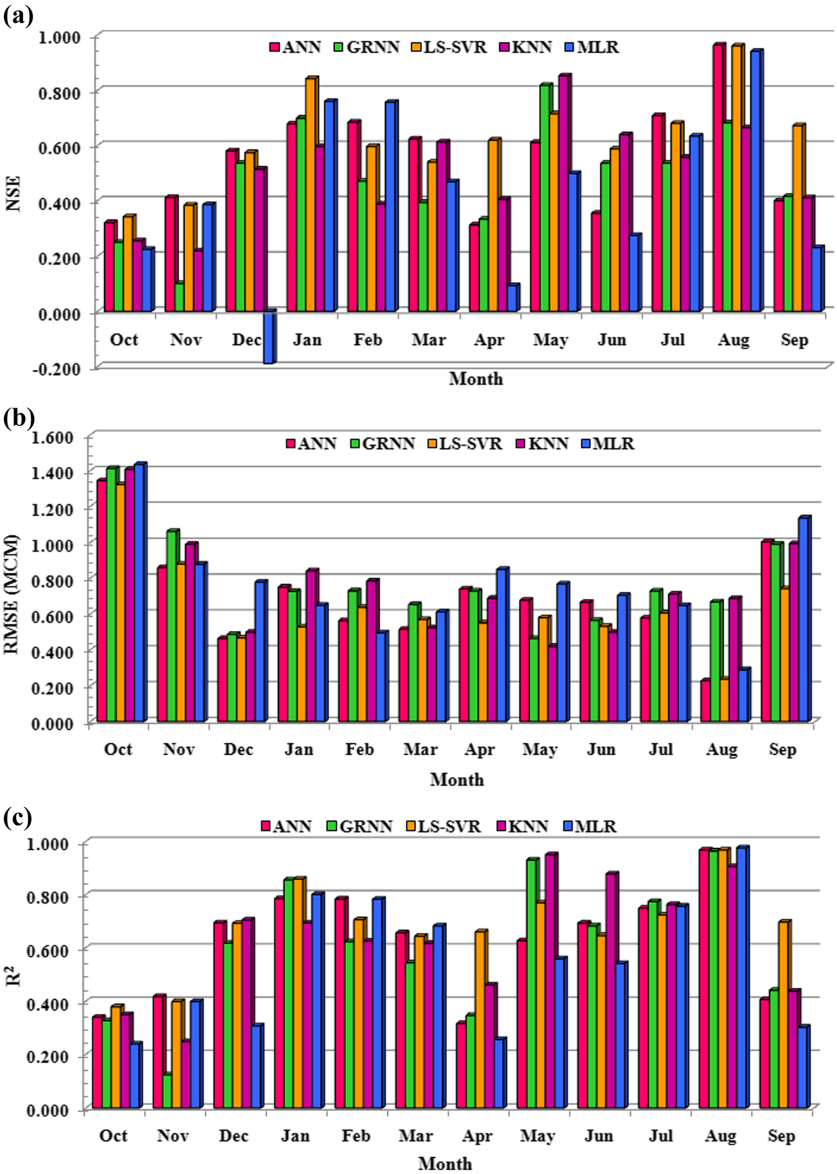

Fig. 3 The results of the forecasting models based on the three assessment criteria including NSE (a), RMSE (b), and R^2 (c)

Table 4 The number of the results in each class of performance based on NSE and RMSE criteria

Performance Rating	Model Efficiency limitation		Model				
	NSE	RMSE	ANN	GRNN	tbcolw30ptLS-SVR	KNN	MLR
Very good	0.75 < NSE ≤ 1	0≤ RMSE≤ 0.5 SD	1	1	2	1	3
Good	0.65 < NSE ≤ 0.75	0.5 SD < RMSE ≤ 0.6 SD	3	2	3	1	0
Satisfactory	0.5 < NSE ≤ 0.65	0.6 SD < RMSE ≤ 0.7 SD	3	3	5	5	1
Unsatisfactory	NSE ≤ 0.5	RMSE >0.7 SD	5	6	2	5	8

and KNN models in 4 months is in the rate of "Very good" and "Good" while that of ANN and LS-SVR in 3 months is in these rates. However, according to this index, the number of linear and nonlinear conditions corresponding to the results of MLR is similar to two other criteria. Also, based on this criterion, the efficiency of LS-SVR is better than other models because of having no results in the rate of "Poor".

A comparative assessment of the models' performance with respect to the optimum values of their parameters obtained from LOOCV, as shown in Table 6, suggests that the pattern between predictor and predicted variables in Apr is specifically complicated because the number of hidden layer neurons of ANN, the value of *K* parameter for KNN, and the value of *Gamma* parameter for LS-SVR is large; however, only LS-SVR has performed in the rate of "Satisfactory" while the performance of other models is in the rate of "Unsatisfactory" in this month.

Moreover, in Jan, Feb, Jul, and Aug that the pattern between predictor and predicted variables is linear (based on the performance of MLR), the optimized structures of all models are simple, other than that of ANN for Jan; nevertheless, the performance of GRNN and KNN in Feb is in the rate of "Unsatisfactory" and in other months it is lower than two other models.

A general evaluation of the optimum structure of the models indicates that ANN model has a relatively complicated structure with the number of hidden layer neurons ≥5 when its performance is in the rate of "Unsatisfactory"; however, in most of other months with better performance, its optimum structure is simpler (less number of neurons). But, in LS-SVR, GRNN, and KNN models, there is not a specific relationship between the performance of the models and the optimum value of their parameters. For example, the *Gamma* parameter of LS-SVR is equal to 0.1 in Jan and Mar while its performance is in the rate of "Very good" and "Satisfactory" in these months, respectively. Also in KNN model, the number of *K* is 10 in Dec and Apr while it performs in the rate of "Satisfactory" and "Unsatisfactory" in these months, respectively. Moreover, the optimum value of *Spread* parameter of GRNN in Mar and

Table 5 The number the results in each class of performance based on R^2 criterion

Performance Rating	R^2	Model				
		ANN	GRNN	LS-SVR	KNN	MLR
Very good	$0.86 < R^2 < 1.00$	1	3	2	3	1
Good	$0.77 < R^2 < 0.85$	2	1	1	1	2
Fair	$0.65 < R^2 < 0.76$	4	1	7	2	2
Poor	$R^2 < 0.64$	5	7	0	6	7

Table 6 The optimized value of the model parameters resulted from LOOCV method

Mouth	ANN Model		LS-SVR Model				GRNN Model	KNN Model		
			Type of optimized Kernel Function	Kernel Parameters*		Gamma		K	Weight of variables	
	Initial Weights	Number of hidden layer neurons		Param 1	Param 2		Spread		w1	w2
Oct	0.5	5	Polynomial	0.2	5.0	5.9	0.2	3	1.0	__
Nov	0.6	6	Polynomial	1.1	1.0	10.3	0.4	5	1.0	__
Dec	0.9	4	Polynomial	0.1	5.0	5.3	1.2	10	1.0	__
Jan	0.1	10	Polynomial	2.0	3.0	0.1	0.3	2	1.0	__
Feb	0.8	5	Polynomial	0.1	5.0	5.0	0.1	2	1.0	__
Mar	0.4	2	Polynomial	0.7	5.0	0.1	0.1	4	1.0	__
Apr	0.1	10	RBF	0.1	___	53.9	0.2	10	0.9	0.1
May	0.3	5	Polynomial	0.9	5.0	10.1	0.1	2	0.1	0.9
Jun	0.6	7	Polynomial	2.0	2.0	3.7	0.2	4	0.6	0.4
Jul	0.9	4	Polynomial	0.6	4.0	6.2	0.1	3	1.0	__
Aug	0.4	3	Polynomial	2.0	4.0	1.3	0.2	4	1.0	__
Sep	0.5	10	Polynomial	1.2	5.0	0.6	0.3	2	0.4	0.6

* Param 1 and 2 for the polynomial kernel functions are constant value (τ) and power (d), respectively while in RBF kernel, param1 is standard deviation (σ)

May is equal to 0.1, which means a closely fitness, whilst its performance is in the rate of "Unsatisfactory" and "Very good" in these two months, respectively.

Since the performances of the models are various in linear and nonlinear conditions in different months based on three criteria, a cumulative evaluation similar to that suggested by Ajmal et al. (2015) is applied in order to do a total assessment of them in each of conditions and total of them. In this method, at first, the models are ranked from 1 to 4 for each month based on each of three criteria such that the best to worst models receive rank 1 to 4, respectively (Table 7). Then, the corresponding score of 8 to 2 are assigned to each model for each month in descending order with 2 score for each rank; such that the best (worst) models in each month receives rank 1 (4) and score 8 (2) based on each of criteria. Totally, the models are ranked in two conditions of linearity and nonlinearity based on the summation of their scores received from each of criteria for the months corresponding to each condition.

Table 7 The ranks of the forecasting models in each month based on each of assessment criteria

Model	Assessment Criteria	Month											
		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
ANN	NSE	2	1	1	3	1	1	4	4	4	1	1	4
	RMSE	2	1	1	3	1	1	4	4	4	1	1	4
	R^2	3	1	2	3	1	1	4	4	2	3	1	4
GRNN	NSE	4	4	3	2	3	4	3	2	3	4	3	2
	RMSE	4	4	3	2	3	4	3	2	3	4	3	2
	R^2	4	4	4	2	4	4	3	2	3	1	3	2
LS-SVR	NSE	1	2	2	1	2	3	1	3	2	2	2	1
	RMSE	1	2	2	1	2	3	1	3	2	2	2	1
	R^2	1	2	3	1	2	2	1	3	4	4	2	1
KNN	NSE	3	3	4	4	4	2	2	1	1	3	4	3
	RMSE	3	3	4	4	4	2	2	1	1	3	4	3
	R^2	2	3	1	4	3	3	2	1	1	2	4	3

Table 8 The cumulative scores and ranks of the forecasting models based on each and all of assessment criteria

Model	NSE		RMSE		R^2		Total Linear Score (Rank)	Total Nonlinear Score (Rank)	Total Score (Rank)
	Linear Score (rank)	Nonlinear Score (rank)	Linear Score (rank)	Nonlinear Score (rank)	Linear Score (rank)	Nonlinear Score (rank)			
ANN	28(1)	38(3)	28(1)	38(3)	24(1)	38(3)	80(1)	114(3)	194(2)
GRNN	16(3)	30(4)	16(3)	30(4)	20(3)	28(4)	52(3)	88(4)	140(4)
LS-SVR	26(2)	50(1)	26(2)	50(1)	22(2)	46(2)	74(2)	146(1)	220(1)
KNN	10(4)	42(2)	10(4)	42(2)	14(4)	48(1)	34(4)	132(2)	166(3)

Table 8 shows the cumulative scores (ranks) of each model in each of linearity/nonlinearity conditions based on each of assessment criteria and total of them.

As can be seen from this table, the ranks of the models are different in linear and nonlinear conditions; in linear conditions ANN model performs best, followed by LS-SVR, GRNN, and KNN models. But in nonlinear conditions, LS-SVR receives rank 1, while KNN, ANN, and GRNN are respectively in the next ranks. However, the total ranks of the models are different from two other conditions; in total conditions, the best performance belongs to LS-SVR, followed by ANN, KNN, and GRNN respectively.

Based on outcomes of this study, it can be said that the ranks of LS-SVR model in nonlinear and total conditions confirm the results of the researches done by Lin et al. (2006), Wang et al. (2009), Kalra and Ahmad (2012), Kalra et al. (2013), Callegari et al. (2015) for the excellence of LS-SVR model than ANN and MLR models. However, the preference of ANN to LS-SVR model in linear conditions is consistent with the results of Bharti et al. (2017) prediction of monthly runoff.

Further, in linear, nonlinear and total conditions, ANN model outperforms GRNN model for monthly streamflow forecasting which is only in agreement with the results of Fallah Haghgoo and Sharifi (2011). Therefore, the results of this study do not confirm the results of Hosseini and Araghinejad (2015), Cigizoglu (2005), and Kisi (2008).

Moreover, the results of nonlinear conditions reveal the preference of KNN to ANN model that is consistent with the results of the research by Wu and Chau (2010) whilst in the linear conditions of monthly forecasting the performance of ANN is better than KNN which confirms the results of Wu et al. (2010) and Mekanik et al. (2013).

In the light of the results above, it can be said that some of inconsistent results achieved from different researches could be due to their different conditions such as linearity, nonlinearity or all of them, while it was not considered in most of them.

5 Summary and Conclusion

In this paper, the performance of two neural network models, i.e. ANN and GRNN, as well as, LS-SVR and KNN models, as the best identifies forecasting models in the previous researches, was evaluated and compared in the equal conditions in terms of the study area, data sets, and the methods of determining the best structure of the models while they were assessed based on various linear and nonlinear patterns of forecasting between predictor and predicted variables in different months. For this purpose, the models were assessed in order to forecast the monthly inflow to the *Karkheh* reservoir, Iran, whilst all of them were applied with their best structure where the absolute optimum values of the effective parameters were determined with the same manner involving Leave-One-Out Cross Validation (LOOCV) method.

The results showed that the rank of the models' performances in linear and nonlinear conditions based on three assessment criteria, i.e. NSE, RMSE, and R^2, is different; in linear conditions, ANN model receives rank 1, followed by LS-SVR, GRNN and KNN models. But in nonlinear conditions, rank 1 belongs to LS-SVR, while KNN, ANN, and GRNN are in the next ranks respectively. However, in total conditions of linearity and nonlinearity for forecasting the inflow to *Karkheh* reservoir, LS-SVR model performed best according to the performance ratings of all criteria. In this respect, ANN was the second better model while KNN and GRNN were in the next, respectively.

Moreover, a comparative assessment of the optimum value of the model parameters and their performances revealed that ANN model had a relatively complicated structure with the number of hidden layer neurons ≥5 when its performance was in the rate of "Unsatisfactory"; while in most of other months with better performance, its optimum structure was simpler (less number of neurons). But, in LS-SVR, GRNN, and KNN models, there was not a specific relationship between the performance of the models and the optimum value of their parameters.

A total evaluation of the results of this study as compared to the previous studies suggested that the inconsistent results of some researches could be because of different conditions such as linearity, nonlinearity or all of them, while it was not considered in most of them. Therefore, it can be concluded that with respect to different conditions of linearity and nonlinearity between predictor and predicted variables, the selection of the models in order to achieve the best forecasts can be different.

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