American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)
ISSN (Print) 2313-4410, ISSN (Online) 2313-4402
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http://asrjetsjournal.org/

Streamflow Forecasting Using Artificial Neural Network and Support Vector Machine Models

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Abstract

This paper investigates the ability of two soft computing methods including artificial neural network (ANN) and support vector machine (SVM) models in modeling monthly streamflow. The results of ANN and SVM models are compared on basis of determination coefficient (R^2), root mean square error (RMSE) and mean absolute error (MAE) to evaluate the performance of the applied models. Comparison of results indicates that the SVM models with RMSE = 147.01 m^3/s, MAE = 86.68 m^3/s and R^2 = 0.872 in test period is superior in forecasting monthly streamflows than the ANN models with RMSE = 161.59 m^3/s, MAE = 94.87 m^3/s and R^2 = 0.869, respectively. It is found that SVM models can be successfully used in predicting monthly streamflows.

Keywords: Streamflow; Soft computing models; ANN; SVM.

1. Introduction

Water scarcity, high demand of electricity consumption, water requirement for the irrigation and the drinking purposes are the key factors that compelled researchers to predict streamflow precisely for efficient usage of water resources.

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Prediction of streamflow plays a key role in economic development of a catchment. Traditionally, streamflow prediction of a river basin is performed using physical and conceptual based models. Hydrological models have been categorized on the basis of their goals and their structures. Data driven models extensively used to model many variables in the field of hydrology, such as prediction of extreme events (e.g. peak and low flows), streamflow or suspended sediment forecasting, reservoir inflow forecasting, precipitation or temperature prediction, evaporation or groundwater or water quality forecasting and rainfall runoff modeling. Artificial neural network (ANN) and support vector machine (SVM) are most popular and extensively used data driven models. These models have ability to incorporate the nonlinear behavior of hydrological time series.There is a plethora of literature on ANN model's applications in the field of hydrology. Many researchers used ANN models to model different variables in the field of water resources. Thus, a complete review of all those application in this paper is not possible. ANN is selected in this study due to its better performance over conventional data driven models in the field of hydrology [1, 2]. An ANN model is applied to forecast river flow in comparison of an analytic power model [3]. They found the neural network model perform better than analytic power model. A neural network model is utilized to forecast river discharges in comparison of a conventional method [4]. They found that ANN prediction results were better than the conventional model. Daily river flows were predicted by using neural network mode [5]. ANN models were utilized in monthly river discharges prediction in comparison of conventional statistical model [6]. He explored that ANN model outperformed the statistical model in predicting streamflow. Different artificial neural network models were applied in comparison of conventional statistical model to predict the streamflow at the Jinsha river basin, China [7]. They found that the ANN models performed better than statistical model. Cigizoglu and Kisi [8] predicted daily streamflow by using ANN models with different training algorithms. In the last decade, support vector machine (SVM) which is one of the soft computational techniques has been successfully used in hydrology and proved as a better alternative to overcome some of the basic lacunae in application of ANN models. Khan and Coulibaly [9] used SVM models to predict lake water levels in comparison of multilayer perceptron (MLP) and multiplicative seasonal autoregressive model (SAR). They found that SVM prediction accuracy is better than the other two models for multi month ahead streamflow prediction. SVM model was applied to forecast long-term streamflow [10]. The river stage was forecasted by using the SVM model [11]. Daily suspended sediments were estimated by using SVM model [12]. Kisi and Cimen [13] predicted daily reference evapotranspiration through SVM model. For optimized reservoir operation, SVM model was successfully applied [14]. Monthly streamflows were predicted by using SVM model [15]. In precipitation downscaling problem, SVM model was utilized. In the literature many researchers used SVM models in comparison of ANN models. Guo and his friends [16] predicted monthly river discharges. They explored that the SVM outperformed than the ANN models. The SVM model was utilized to estimate the removal efficiency of settling basins in canals in comparison of ANN models [17] and found that SVM reduced the root mean square error of ANN from 5.736 to 5.712 due to its use of the structural risk minimization principle. SVM is used to forecast flood stage by Liong and Sivapragasam [18] in comparison of ANN models.

They found that predicted error by SVM for forecasted flood stage is less in comparison of ANN models. The purpose of this paper is to investigate the performance of SVM model for monthly streamflow forecasting and to compare this with the performance of ANN models.

2. Study Area and Data

Dainyor hydraulic station is selected in this research to test the predicting ability of the ANN and SVM models. Dainyor hydraulic gauging station is an important gauging station of upper Indus Basin and covers a drainage area of 13,734 Km^2. Map of Dainyor gauging station is explained in Fig. 1. The monthly streamflow data of Dainyor gauging station from 1968 to 2006 is used in this study to forecast monthly streamflow. For the monthly streamflow forecasting applications, the monthly observed data of Dainyor station from 1968 to 1997 is used as training and from 1998 to 2006 is used as testing. The observed monthly streamflows show high positive skewness (1.347). The auto-correlations are quite low showing low persistence (e.g., lag1= 0.734, lag2= 0.223).

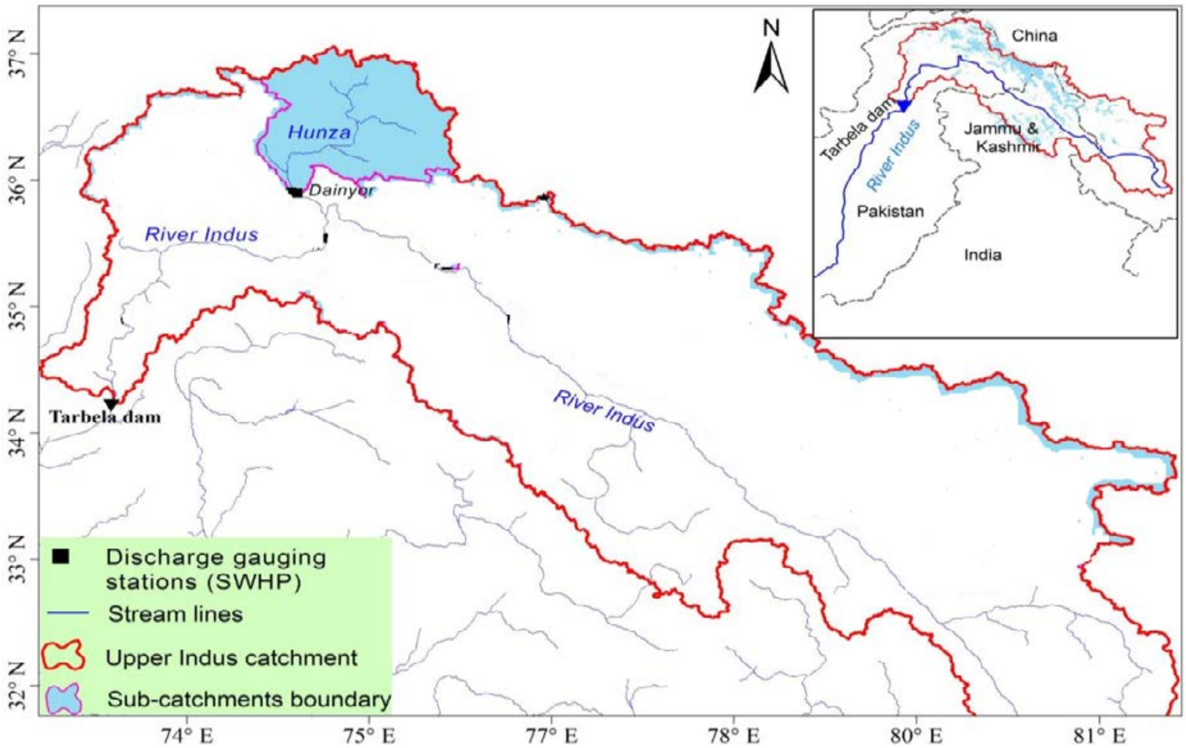

Figure 1: Location map of study site

Table 1: Monthly statistics of streamflow data sets

Data Set	Min	Max	Mean	S.deviation	Skewness	Lag1	Lag2	Lag3
Whole data set	34.38	1850	281.1	325.5	1.347	0.734	0.223	-0.206
Training data set	35.25	1759	360.5	471.3	1.121	0.693	0.165	-0.216
Testing data set	34.38	1850	285.6	347.9	1.533	0.714	0.196	-0.204

3. Methodology

3.1 ANN

Arificial neural network (ANN) models are biologically inspired computational models and the development of these models originated with understanding the brain's way to perform tasks. ANN models are biologically inspired computational models and the development of these models originated with understanding the brain's way to perform tasks. The research on ANN models started with a classic paper by McCulloch and Pitts [19] in which they designed a neural model. A major development in the field of ANNs models was found in 1949,when Hebb [20] proposed many ANN architectures and also developed the learn rule known as "postulate of learning". However, these both researches was biologically focused, not focus the computationally ability of ANN models. Later in 1960s, Rosenblatt [21] focused this issue in his studies by contributing the perceptron learning theorem i.e. commonly known as single layer feed forward neural network (FFNN) these days. However, Minsky and Papert [22] exposed the limits of this theorem due to having no extra layer to model complex functions. The most significant development in the field of NN models was the re-discovery of back propagation algorithm after 1980 by adding extra layer to single layer perceptron, which has emerged as the most popular learning algorithm for multilayer perceptrons. Back propagation algorithm was firstly developed by Werbos [23] in his Ph.D. thesis in 1974. However, his research was unknown for over a decade and gained popularity after the research work of Rumelhart and his companions [24]. The multilayer perceptrons or FFNN model is the most generally used ANN model [25]. Figure 2 illustrate a three-layer neural network consisting of layers i, j, and k, with the interconnection weights Wij and Wjk between layers of neurons. Initial estimated weight values are progressively corrected during a training process that compares predicted outputs to known outputs, and back-propagates any errors (from right to left in Fig. 2) to determine the appropriate weight adjustments necessary to minimize the errors.

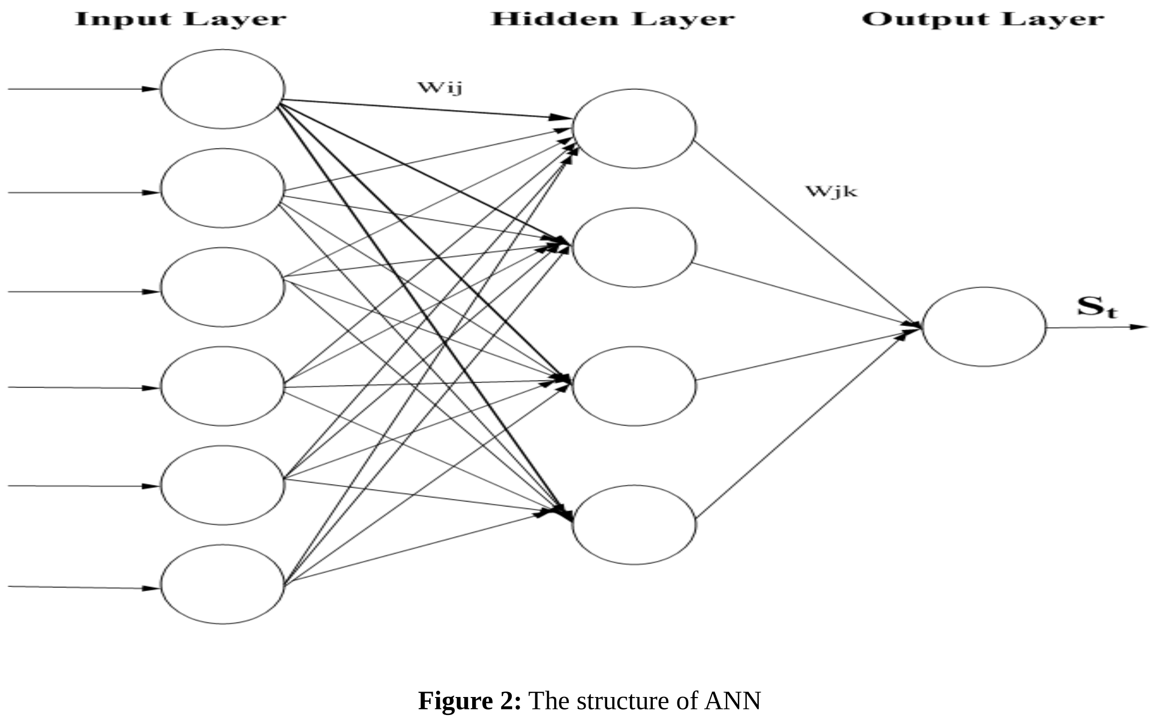

Figure 2: The structure of ANN

3.2 SVM

The idea of support vector machines (SVMs), which are known as the classification and regression procedures, has been developed by Vapnik [26]. Support vector regression (SVR) is used to describe regression with SVMs in the open literature. In regression estimation with SVR we attempt to estimate a functional dependency of y(x) on x inputs. The regression estimation with SVR is to estimate a function according to a given data set (x,y), where x denotes the input vector; y denotes the output (herein, the input vectors (x) refer to lagged values of streamflow, whereas the target values (y) refer to forecasted values). The regression function uses the following function:

$$y(x) = \omega^T \varphi(x) + b \tag{1}$$

where $\varphi(.)$ is a nonlinear function by which x is mapped into a feature space, b and x denote a weight vector and a coefficient that have to be estimated from the data.

4. Results and Discussion

In this study, the SVM and ANN models were tested in one month ahead streamflow forecasting. Three input combinations based on lagged monthly streamflow values were selected in this study. Let assume that the SF_t represents the flow at time t, the input combinations selected in the study are; (i) SF_{t-1},(ii) SF_{t-1}, SF_{t-2}, (iii) SF_{t-1}, SF_{t-2} and SF_{t-3}. The models performance was evaluated with respect to root mean square errors (RMSE), mean absolute errors (MAE) and determination coefficient (R^2) statistics for each input combination. The RMSE , MAE and R^2 can be expressed as;

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(SF_o - SF_f)^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|SF_o - SF_f\right| \tag{3}$$

$$R^2 = \left[\frac{\sum_{t=1}^{N}(SF_o - \overline{SF_o})(SF_f - \overline{SF_f})}{\sqrt{\sum_{t=1}^{N}(SF_o - \overline{SF_o})^2\,(SF_f - \overline{SF_f})^2}}\right]^2 \tag{4}$$

Where N is the total number of observations, SF_o is observed flow, SF_f is forecasted streamflow, $\overline{SF}_o$ is average of streamflow and $\overline{SF}_f$ is average forecasted flow.

Before testing the data, the architecture of ANN and the parameters for the SVM model (C and sigma) determined by using trial and error procedure. However, the trial and error procedure for SVM’s parameters determination converges very quickly while ANN took more time to obtain optimal architecture for the given training set. Table 2 shows the test results of the SVM models using the different input combinations for the

Dainyor station.

Table 2: The RMSE, MAE and R^2 statistics of SVM models using different streamflow input combinations

Model inputs	Training period			Testing period		
	RMSE	MAE	R^2	RMSE	MAE	R^2
SF_{t-1}	219.32	170.97	0.561	238.81	176.15	0.539
SF_{t-1}, SF_{t-2}	147.91	102.56	0.869	151.36	105.42	0.859
SF_{t-1}, SF_{t-2}, SF_{t-3}	140.43	91.75	0.896	147.01	86.68	0.872

According to the performance of the SVM models, the SVM model provides give better accuracies for the input combinations (iii) than the input combination (i) and (ii). The test results of the ANN models using the different input combinations for the Dainyor station is given in Table 3. It is clear from the table that ANN models also gives better forecast results for the input combination (iii) in comparison of input combination (i) and (ii). However, the input combination (i) shows worse results for both soft computing models.

Table 3: The RMSE, MAE and R^2 statistics of ANN models using different streamflow input combinations

Model inputs	Training period			Testing period		
	RMSE	MAE	R^2	RMSE	MAE	R^2
SF_{t-1}	229.36	159.24	0.579	240.53	159.42	0.559
SF_{t-1}, SF_{t-2}	193.01	125.62	0.851	174.39	109.21	0.853
SF_{t-1}, SF_{t-2}, SF_{t-3}	167.08	100.17	0.888	161.59	94.87	0.869

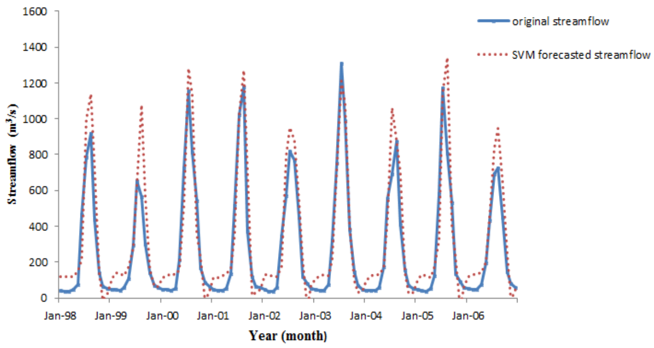

Figure 3: Flow hydrograph between original streamflow and forecasted streamflow using SVM

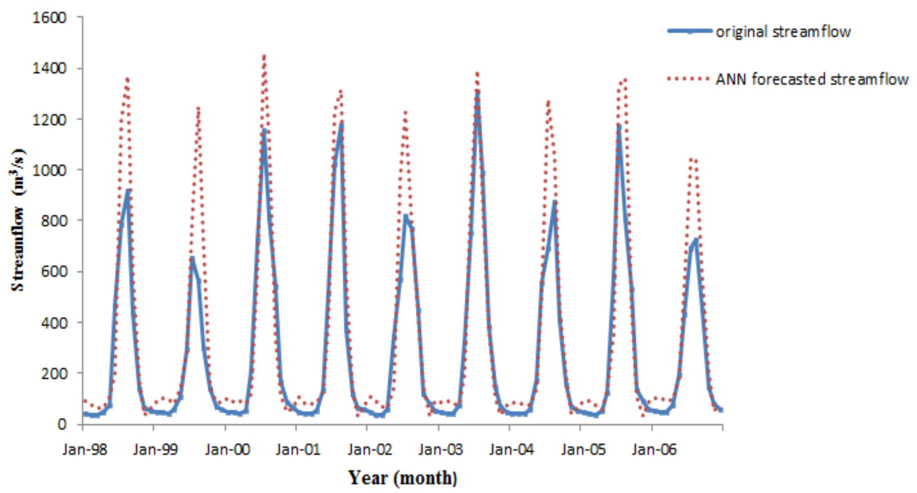

Figure 4: Flow hydrograph between original streamflow and forecasted streamflow using ANN

Comparison of Tables 2 and 3 reveals that SVM models perform better than ANN models during the training and testing period for all the input combinations. The average RMSE accuracies of the ANN models for the training and testing data sets were increased by 12.7–11.6 %, respectively using the SVM models for the Dainyor station. The hydrographs between original and forecasted streamflows by the SVM and the ANN models are presented in Figs.4 and 5, respectively. It is also evident from the hydrographs that the predicted streamflow by SVM is in good fit with the original streamflow in comparison of that ANN model.

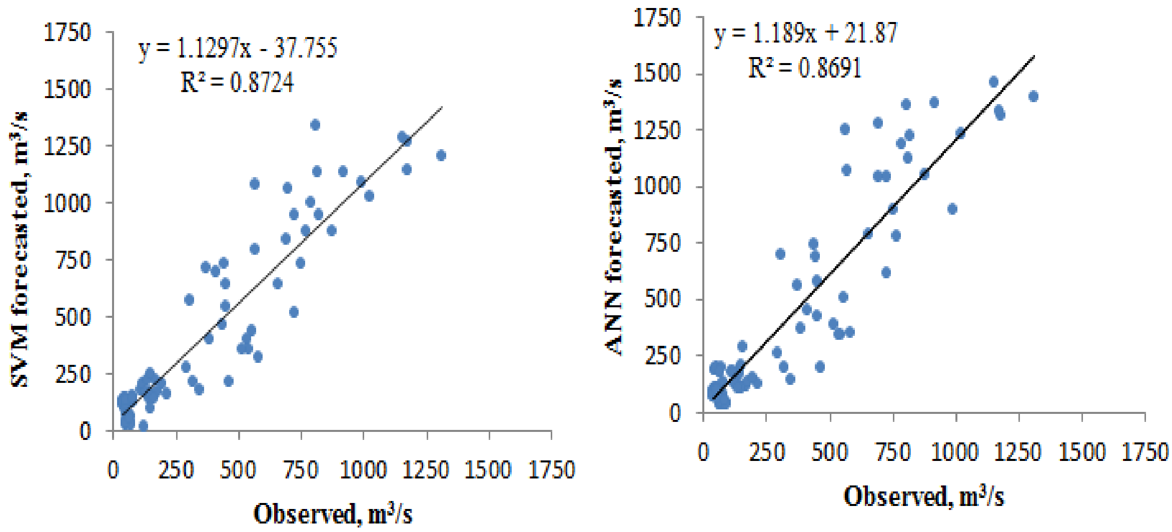

Figure 5: Scatter plots of forecasted streamflow using SVM and ANN models

The observed and forecasted monthly streamflows by the SVM and ANN models for the input combination (iii) data are shown in Fig. 5 in the form of scatterplot. It is clear from the scatterplots that the fit line coefficients a and b (assume that the fit line equation is y=ax+b) of the SVM model are respectively closer to the 1 and 0 with a higher R^2 value than that of ANN model.

5. Conclusions

In this paper, the performance of SVM and ANN models is compared in predicting of monthly streamflows. According to the results, it was found that SVM models for all different input combinations provided better prediction results in comparison of the ANN models for monthly streamflow prediction. The SVM model improved the average error value (RMSE) with respect to the ANN model by 12.7 and 11.6 % for the training and testing data sets, respectively. The results indicated that the SVM performed better than the ANN models. It is due to SVM's inherent properties i.e. no specific architecture requirement for SVM model at training stage and also by using structural minimization principle that helps it to avoid get local minima. Thus, SVM models could be successfully used in predicting monthly streamflows at this study site**.**

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