https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

Application of Support Vector Machine for River flow Estimation

Reza Dehghani*[1], Hassan Torabi Poudeh[2]

[1]Phd student, Department of Water Engineering, , university of lorestan,Iran
[2]Associate Professor of Water Engineering, University of Lorestan, Khorramabad, Iran
*Corresponding author

***Abstract*— *In recent years application of intelligent methods has been considered in forecasting hydrologic processes. In this research, month river discharge of kakareza, a river located in lorestan province at the west of Iran, was forecasted using Support vector machine and as genetic programming Inference System methods in dehno stations. In this regard, some different combinations in the period (1979-2015) as input data for estimation of discharge in the month index were evaluated. Criteria of correlation coefficient, root mean square error and Nash Sutcliff coefficient to evaluate and compare the performance of methods were used. It showed that combined structure by using surveyed inelegant methods, resulted to an acceptable estimation of discharge to the kakareza river. In addition comparison between models shows that Support vector machine has a better performance than other models in inflow estimation. In terms of accuracy, Support vector machine with correlation coefficients (0.970) has more propriety than root mean square error (0.08m^3 /s) and Nash Sutcliff (0.94) . To sum up, it is mentioned that Support vector machine method has a better capability to estimate the minimum, maximum and other flow values.*

***Keyword*— Genetic Programming, Estimate, Kakareza River, Support Vector Machine**

I. INTRODUCTION

Nowadays one of the most important issues for managing flood and preventing the economic and physical damage caused by it, are correctly prediction the river flows. Accurate estimates of inflow to reservoirs could play an important role in the planning and management of water resources. But factors and various effects that have an influence on this phenomenon that analysis makes difficult. The statistical Models and the regression models are the most commonly analytical techniques that frequently according to a linear resolution of these phenomena presented results along with error and cannot model with acceptable accuracy temporal changes the phenomenon. So choose a model that could using affective factors, estimates acceptable the input current seems imperative. Recently artificial intelligent (AI) techniques have been applied to estimate/predict the discharge(Kisi and Cobaner 2009). These AI techniques are simple, robust and can handle complex non-linear processes with ease. From the literature, it is seen that the AI techniques such as gene expression programming (GEP), support vector machines (SVM), etc. were used to predict the discharge(Wang et al. 2008). As they are fully non-parametric, AI techniques have a major advantage that they do not require a priori concept of the relations between the input variables and output data (Bhagwat and Maity 2012). A classical feature of AI is that the models that are able to analyze the stochasticity, dynamicity, patterns and attributes in the input variables used to simulate the evaporation data, and so, are considered more feasible over the other methods of the estimating of discharge data (e.g. experimental approaches and physically-based models).

Examples using the SVM capability include: Stage–discharge modeling (Barzegar et al 2019;Sahoo et al 2019; Elkiran et al 2019; Rezaei et al 2019; Adnan et al 2019; Fathian et al 2019; Yassen et al 2018; Imani et al 2018; Tongal et al 2018; Ghorbani et al 2016;Londhe and Gavraskar 2018;Ghazvinei et al 2017; Karahan et al2014; He et al 2014).

In a research, Presented appropriate method for seasonal flow discharge and horary used by SVM, in the research using the amount of snow equivalent water and the volume of the previous periods, forecasted amount volume flow for the six-month time scales and 24-hour than the result showed satisfactory model (Asefa et al.2005). Using by genetic programming were modeled the process rainfall-runoff with daily data in two fairly big China basin that results of GP showed good agreement

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

with real data (Jayawardenaet al.2005). In this paper, the support vector machine (SVM) is presented as a promising method for hydrological prediction. Through the comparison of its performance with those of the ARMA and ANN models, it is demonstrated that SVM is a very potential candidate for the prediction of long-term discharges(Lin et al,2006). Also in order to forecasts daily discharge flow Shevell river in America used of genetic programming and artificial neural network and showed both methods had acceptable results but GP has relatively higher precision than artificial neural network (Guven.2009). Support Vector Machine (SVM) is used to forecast daily river flow and the results of these models are compared with observed daily values. The results showed a good performance in network support vector machine is estimating the daily discharge(Moharrampour et al.2012).

In total, according to the researches done and the fact that the river Kakareza is one of the most important rivers in Lorestan province and the most important source of water supply to different parts of its neighboring areas, which over the past decades has reduced the flow rate of the river in the basin, which can be explained by lower river basin fluxes and surface flows. Therefore, the importance of river discharge modeling and management measures to improve its water quality is more than necessary. Therefore, the aim of this study was to estimate the discharge of Kakareza River using a support vector machine based on the use of the principle of inductive minimization of structural error. In simulation, the learning method with monitoring in radial base functions makes estimating the parameter of high speed and error Less than other kernel functions.(Vapnik,1995;Vapnik,1998).

II. MATERIALS AND METHODS

Case study and used data

Study area is kakareza river in the province of Lorestan, Iran. this river is one of permanent rivers in the province and is originated from southeastern mountains of aleshtar and biranshahr (dehno). When this river passes through aleshtar suburbs it is known as kakareza. The river is between "15 ° 48 ° 49 ° longitude to the" 22 ° 32 to "52 ° 33 degrees latitude and it flows across the east of Khorramabad (capital city of Lorestan Province). This river is one of initial branches of karkhe river in zagros mountains and have the average altitude of 1550 meters above sea level. kakareza river basin area is about 1148 square kilometers and its river has a length of 85 km. kakareza river joins Kashkan, Cimmeria, and Karkhe rivers in its way and eventually pours into the Persian Gulf. The geographical location of the study area is shown in Figure 1. In this study, available runoff data at monthly scale of horod station (kakareza) from 1979 to 2015 in Lorestan Regional Water was used. Table 1, the statistical properties of kakareza river is shown during the mentioned period.

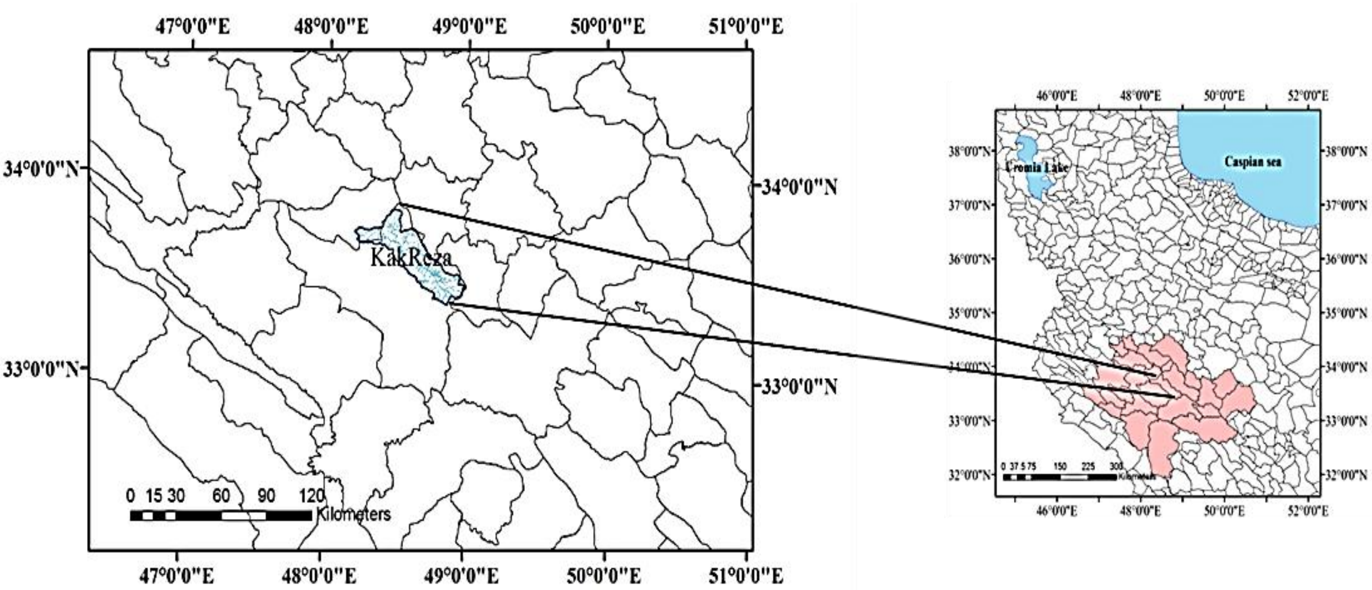


Fig 1. Geographical location kakareza river

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

Table1. Statistical properties discharge parameter daily discharge (1979-2015)

Parameter	Training			Testing		
	Minimum	Mean	Maximum	Minimum	Mean	Maximum
Q	0.01	2.718464	25.15	0.05	1.701161	21.69

One of the most important steps in modeling, is select the right combination of input variables. Also shown in Table 2.The structure of input combinations.

Table2.The structure of input combinations

Structure	Input	Output
1	Q(t-1)	Q(t)
2	Q(t-1)Q(t-2)	Q(t)
3	Q(t-1)Q(t-2)Q(t-3)	Q(t)
4	Q(t-1)Q(t-2)Q(t-3)Q(t-4)	Q(t)

In this Table Q(t-4), Q(t-3), Q(t-2), and Q(t-1) are respectively discharge in t-4, t-3, t-2, and t-1 time as input and Q(t) is discharge in t time as output being considered. Due to the significant cross-correlation between input and output data, in order to achieve an optimal model to estimate the inflow to kakareza river use of different combinations of input parameters that showed them in Table3. To estimate input discharge kakareza river using by Gene Expression Programming and Support Vector Machine with have catchment hydrometric data from 432 registered records during the period (1979-2015), count in 345 records to training and 87 remaining records to verification.

Table 3.Correlation between input and output parameters

	Q(t-1)	Q(t-2)	Q(t-3)	Q(t-4)
Q(t)	0.980	0.964	0.928	0.784

Gene Expression Programming

Gene Expression Programming method presented with Ferreira in 1999 (Ferreira.2001). This method is a combination of genetic algorithms (GA) and genetic programming (GP) method than in this, simple linear chromosomes of fixed length are similar to what is used in genetic algorithm and branched structures with different sizes and shapes aresimilar to the decomposition of trees in genetic programming.Since this method all branch structures of different shapes and size are encoded in linear chromosome with fixed length, this is equivalent than Phenotype and Genotype are separated from each other and system could use all evolutionary advantagesbecause of their. Now,however the Phenotype in GEP included branch structures used in GP, but the branch structures be inferences by GEP (than also calledtreestatement) are explainer all independent genomes. In short can say improvements happened in linear structure then is expressed similar with tree structure and this causes only the modified genomemoved to the Next Generation and don't need with heavy structure to reproduce and mutation (Ferreira.2001). In this method different phenomena are modeling by collection of functions and terminals. Collection of functions generally include the main functions of arithmetic {+, -, ×, /}, the trigonometric functions or any other mathematical function {√, x2, sin, cos, log, exp, …} or defined functions by author whom believed they are appropriate for interpreting model. Collection of terminals consist problem's constants values and independent variables (2001). For applying gene expression programming method is used GenXproTools 4.0 Software. In order to obtain more information can recourse to (Ghorbaniet al.2012).

Support Vector Machine

Support Vector Machine is anefficient learning system based on optimization theory that used the principle of induction minimization Structural error and results an overall optimal solution(Vapnik,1998). In regression model SVM is estimated function associated with the dependent variable Y as if is afunction of several independent variables X(Xu et al.2007).Like other

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

regression problems is assumed the relationship between the dependent and independent variables to be determined with algebraic function similar f(x) plus some allowable error (ε).

$$f(x)=W^{T}.\emptyset(x)+b \quad (1)$$

$$y=f(x)+noise \quad (2)$$

If W is coefficients vector, b is constant characteristic of regression function, and also $\emptyset$ is kernel function, then goal is to find a functional form for f(x). It is realized with SVM model training by collection of samples (train collection). To calculate w and b require to be optimized error function in ε-SVM with considering the conditions embodied in Equation 4(Shin et al.2005).

$$W^{T}.\emptyset(X_i)+b-y_i \le \varepsilon+\varepsilon_i^{*}, \frac{1}{2}W^{T}.W + C\sum_{i=1}^{N}\varepsilon_i + C\sum_{i=1}^{N}\varepsilon_i^{*} \quad (3)$$

$$y_i - W^{T}.\emptyset(X_i) - b \le \varepsilon + \varepsilon_i, \varepsilon_i, \varepsilon_i^{*} \ge 0, \quad i = 1,2,\dots,N \quad (4)$$

In the above equations, C is integer and positive, that it's factor of penalty determinant when an error occurs. $\emptyset$ is kernel function, N is number of samples and two characteristics ε_i and ε_i^* are shortage variables. Finally can rewrite SVM function as follow(Shin et al,2005):

$$f(x)=\sum_{i=1}^{N}\bar{\alpha}_i\,\emptyset(x_i)^{T}.\emptyset(x)+b \quad (5)$$

Average Lagrange Coefficients $\bar{\alpha}_i$ in characterized space is $\emptyset(x)$.Maybe calculation be very complex. To solve this problem, the usual process of SVM model is choose a kernel function as follow relation.

$$K(X_J, X)=\emptyset(X_i)^{T}\sqrt{b^2-4ac} \quad (6)$$

Can be used of different kernel functions to create different types of ε-SVM. Various kernel functions used in SVM regression models are: Polynomial with three Characteristics of the target, Radial Basis Functions (RBF) with one Characteristics of the target, and Linear respectively, are calculated as follows relation(Vapnik.1998).

$$k(x_i,x_j)=(x_i.x_j)^{d} \quad (7)$$

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \quad (8)$$

$$k(x_i,x_j)=x_i.x_j \quad (9)$$

Evaluation Criteria

In this research to evaluate the accuracy and efficiency of the models was used indices Correlation Coefficient (CC), Root Mean Square Error (RMSE), Nash–Sutcliffe coefficient (NS), and Bias according to the following relations.Best values for these four criterions are respectively 1, 0, 1, and 0.

$$CC=\frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\sum_{i=1}^{N}(y_i-\bar{y})^2}} \qquad -1\le R\le 1 \quad (10)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2} \quad (11)$$

$$NS=1-\frac{\sum_{i=1}^{N}(x_i-y_i)^2}{\sum_{i=1}^{N}(x_i-\bar{y})^2} \qquad -\infty\le NS\le 1 \quad (12)$$

In the above relations x_i and y_i are respectively observed and calculated values in time step i, N is number of time steps, $\bar{x}$ and $\bar{y}$ are respectively mean observed and calculated values.

III. RESULTS AND DISCUSSION

The general purpose of intelligent models is to express the relation between variables that find their complexity difficult in the nature of work with high uncertainty. Daily stream flow is one of the important hydrological parameters that is of great importance in future steps. In order to reduce the error and also to estimate the daily flow rate parameter with high accuracy using the lowest input parameters, this method has been used which will provide a better performance compared to approximate methods. The aim of this study is to obtain this natural complexity between hydrological parameters and provide a model for prediction in the future, because daily discharge is more important than other parameters, so this parameter is selected as the target variable.

The results of Gene Expression Programming

Using gene expression programmingdue to the selection of variables in the model and remove variables with less impact and also ability to provide a clear relationship were considered to estimating inflow to the kakareza river. Since ever four input areincorporated to determining the significant variables and more reviews in addition four of the original operator (F1) and the states based on arithmetic operators default (F2). The reason for choice this type of operator has been based on studies (Ghorbaniet al.2012) and (Khatibi et al.2012).

$$F1:\{+,-,*,/,\sqrt{\ },Exp,Ln,^2,^3,\sqrt[3]{\ },Sin,Cos,Atan\} \quad (13)$$

$$F2:\{+,-,*,/\}(14)$$

Results of gene expression programming model for both operator in Table4 show that F2 operator in both stages training and verification with maximum correlation coefficient R=0.88, root mean square error RMSE=0.15 and NS=0.76 has high accurate than other operators. Therefore gene expression programming with F2 operator

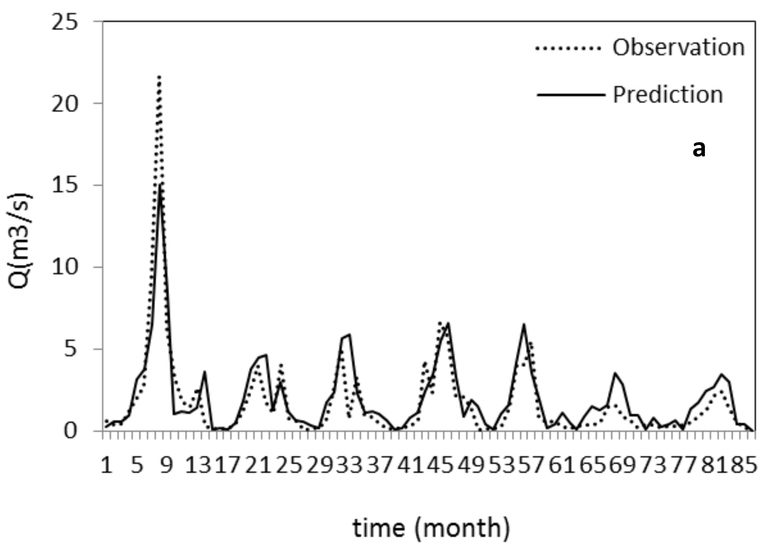
https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

include four the main mathematical operators with a simple mathematical relationship has the most accurate to estimating inflow to the kakareza river. The scatter plots of gene expression programming related to the verification stage in Fig(2-b) showthe fit line of computational values with four mathematical operators to the best fit line y=x.As is clear from this Fig, all of the estimated and observation values are in the fit line except few points that are not inbisector line which it isdenoted the estimated and observed values of equality on the line (y=x). The operation of gene expression programming is acceptable to estimating inflow, it should be noted this model worked fine, meanwhile these values estimate equal to actual values.

These results are consistent with Kisi and Shiri (2012) research. And it can be stated that the equation obtained from gene expression planning is obtained from the random combination of the sum of the terminals and functions. Therefore, if the relationship between inputs and outputs is linear, but the operators sin, cos, etc. are selected in the set of functions, the gene expression planning uses the selective operators to extract the relationship, which reduces the accuracy of the model. In this study, to increase the precision of the model of the operators' sin, cos, and so on, and with accuracy and simplicity, the model derived from four basic mathematical operations was proposed to estimate sediment load.

Table 4. The results of the planning model of gene expression programming using two sets of selected mathematical operator

Number	Model	Training			Testing		
		R	RMSE (m^3/s)	NS	R	RMSE (m^3/s)	NS
1	F1	0.70	0.31	0.63	0.76	0.25	0.64
	F2	0.73	0.32	0.64	0.78	0.23	0.66
2	F1	0.75	0.38	0.68	0.80	0.22	0.68
	F2	0.76	0.34	0.69	0.80	0.21	0.71
3	F1	0.79	0.26	0.71	0.82	0.19	0.72
	F2	0.80	0.21	0.73	0.84	0.19	0.73
4	F1	**0.80**	**0.19**	**0.73**	**0.87**	**0.15**	**0.76**
	F2	0.82	0.15	0.75	0.88	0.15	0.76



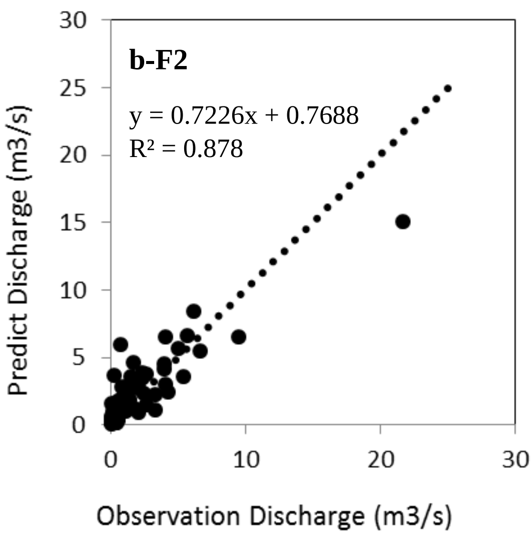


Fig 2. The resulting chart of optimal values of gene expression programming model to the data step verification. a) Computational and observational values of time. b) The scatter plot between estimated and observed values

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

The results support vector machine

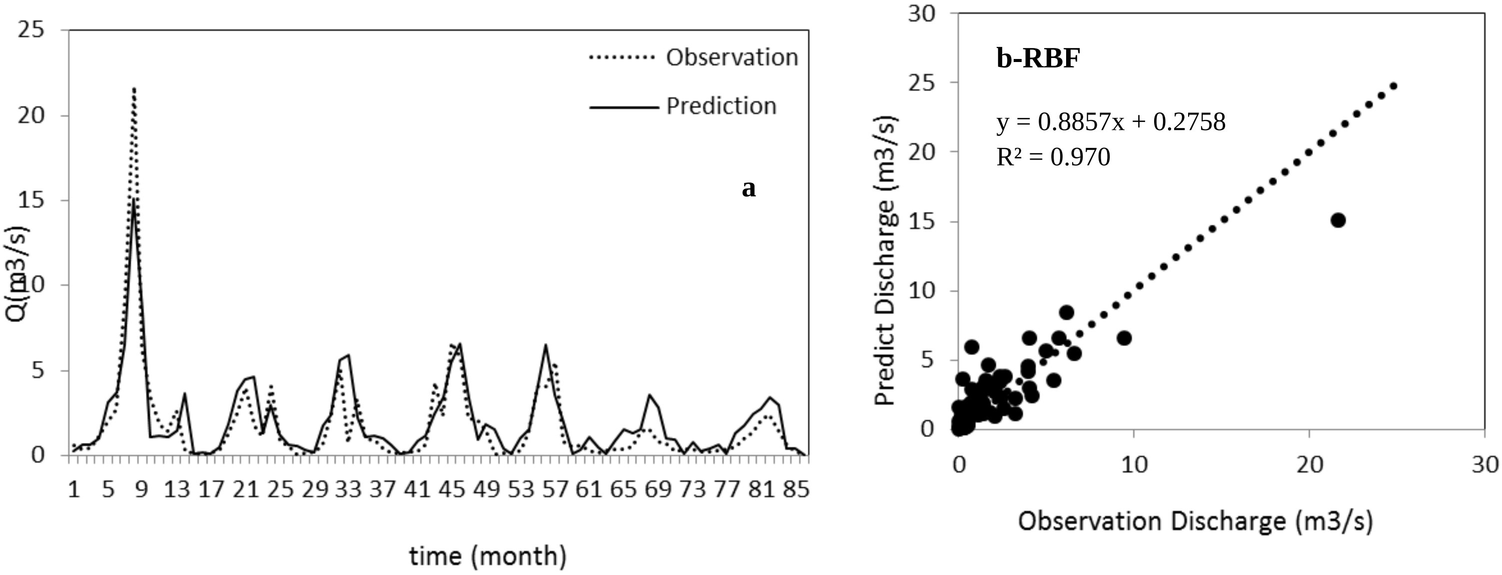
In order to estimate the inflow to the kakareza river by SVM model can examine types of kernel function, than was selected linear kernel, polynomial and radial basis functions that are common types used in hydrology. The results of study models is given in Table5. According to this table combined model number4 with radial basis functions kernel has the highest correlation coefficient R=0.97, lowest root mean square error RMSE=0.08 m^3/s and NS=0.94 in verification stage that has optimal solution than other models. In Fig3 shown the best model for verification of data.

As shown in Fig(3-b) is clear computational values discharge of the support vector machine model verification corresponded with observed values. In this Fig can be seen insignificant difference some of values with the best fit line y=x. According to the diagram (3-a) can be seen high capability of the model. Also, according to Table 5, a high performance support vector machine has been shown in the Kakareza River discharge estimation, even if only one input parameter is used, which leads to the presence of statistical deficiencies in this network with Having the minimum input parameters, such as flow rate, one day before, would have acceptable performance in flow rate forecasting. In Fig. 3, changes in computational and observational values of time are shown, it is seen that this model was in the estimation of most of the values of acceptable accuracy in such a way that these estimates are close to their actual value. The results are consistent with the research by Buyukyildiz and Kumcu (2017) and Nourani et al (2015). This can be explained by the fact that the backup machine is based on the use of the principle of inductive minimization of structural error. Therefore, in simulation, using a learning method with monitoring in radial base functions, the prediction of the parameter has a higher velocity and less error than other kernel functions, and this is a privilege of radial base functions.

Table 5. Results of the three kernel methods used in Support Vector Machine for training and verification data

Number	Kernel	Training			Testing		
		R	RMSE (m^3/s)	NS	R	RMSE (m^3/s)	NS
	RBF	0.87	0.13	0.76	0.90	0.16	0.88
1	Poly	0.74	0.19	0.67	0.79	0.17	0.80
	Line	0.64	0.24	0.54	0.71	0.29	0.69
	RBF	0.89	0.12	0.80	0.93	0.11	0.90
2	Poly	0.76	0.17	0.69	0.81	0.16	0.82
	Line	0.67	0.22	0.58	0.75	0.27	0.71
	RBF	0.90	0.11	0.81	0.94	0.10	0.92
3	Poly	0.79	0.15	0.75	0.81	0.14	0.84
	Line	0.69	0.18	0.62	0.79	0.27	0.72
	RBF	**0.91**	**0.09**	**0.82**	**0.97**	**0.08**	**0.94**
4	Poly	0.81	0.14	0.75	0.84	0.13	0.87
	Line	0.80	0.18	0.66	0.80	0.26	0.73

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817



covered minimum, maximum, and middle values.

Table 6. The final results of the training and verification gene expression programming and support vector machine

Model	Training			Testing		
	R	RMSE (m3/s)	NS	R	RMSE (m3/s)	NS
S.V.M	0.91	0.09	0.82	0.97	0.08	0.94
GEP	0.82	0.15	0.75	0.88	0.15	0.76

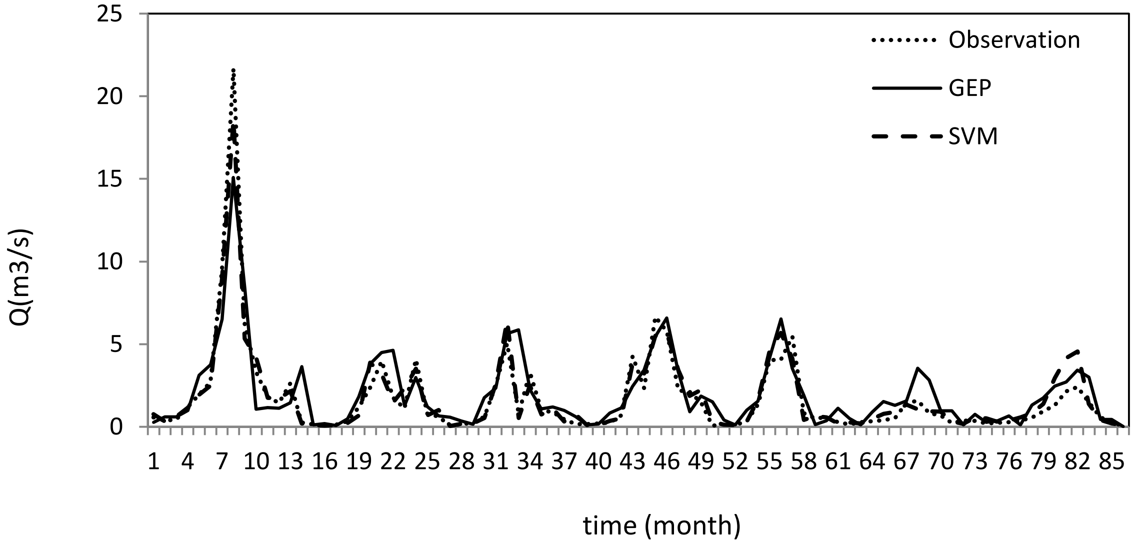


Fig 4. The scatter plot between estimated and observed values gene expression programming and support vector machine models for recorded data in verification stage

https://dx.doi.org/10.22161/ijebm.4.2.1 ISSN: 2456-7817

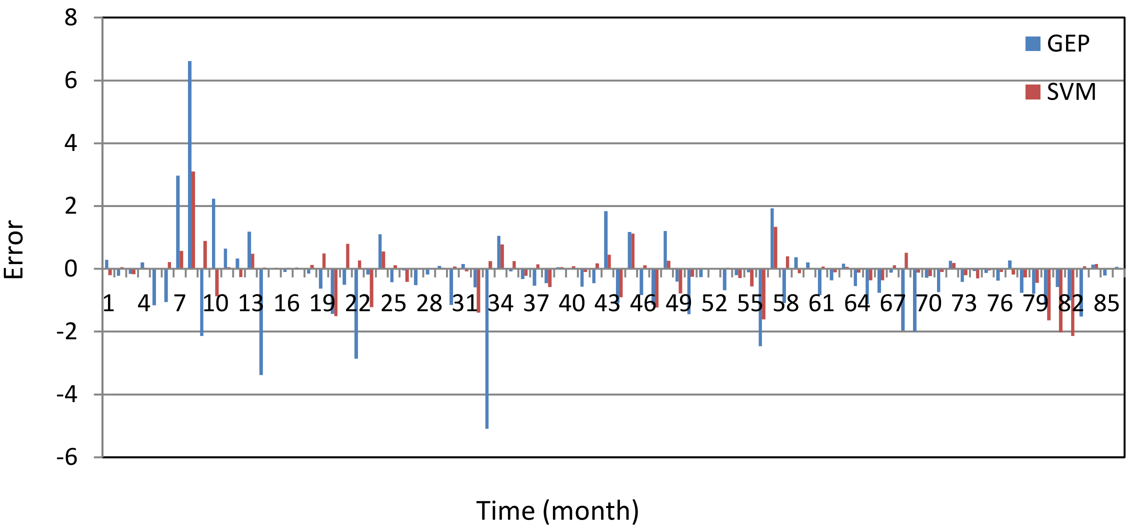


Fig 5. All two models graph optimization error as a percentage of the mean observed value

Finally difference between the observed inflow values and optimal computational models calculated as a percentage of the mean observed values (error value) and was drawn this diagram in comparison with the data recorded (Fig5). As seen in this Fig, more errors to ever three models has been ±5 band the highest error rate gene expression programming and support vector machine models are respectively 6.61 and3.10 percent of the mean observed values. Among these models (GEP and SVM) svm model has lowest error value. Totally due to the high estimation accuracy and reliability gene expression programming and support vector machine models the correlation between the observed values and the computed values are respectively 0.970 and 0.880. Also the results of was significant estimated and observed values in the probability levels %5 and %10 shown, SVM model has significant correlation in both probability levels.

IV. CONCLUSIONS

In this research, we tried to evaluated performance some models to simulating discharge to the kakareza river In the province lorestan using by discharge month data in kakareza river. Used models include gene expression programming and support vector machine models. Observed inflow values compared with estimated inflow in these models (GEP and SVM). The results summarized as follows:

A: SVM model has high accurate and a little error to estimate minimum, maximum, middle values and peak discharge, and high correlation with the observed value. B: Gene expression programming model with the four basic arithmetic operations has high ability to estimating minimum, maximum, and middle values and peak values, also support vector machine with radial basis functions kernel has high ability estimating minimum and middle values but to estimating maximum values doesn't have enough operation. C: Increasing the number of parameters in the various models to simulating inflow cause to improve operation to estimating inflow. D: Estimating inflow using by combined models have lower error and high correlation than other models to estimated inflow in reservoirs dam.

Totally the results of this research showed support vector machine method has highest accurate than other models. As research results (Ghorbaniet al.2016),(Moharrampour et al.2012) and (Asefa et al.2005) has been proven its. Also this research shown using of gene expression programming and support vector machine models could use to estimating inflow to the river.

V. ACKNOWLEDGMENTS

The authors are very grateful of the Regional Water Company, Lorestan Province, Iran, because they participate in gathering the data required to perform the work.

FUNDING

The University of Lorestan, Khorramabad, Iran , supported our research work (Grant No. 1).

Compliance with ethical standards

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

REFERENCES

[1] Adnan M, Liang Z, Heddam S, Zounemat Kermani M, Kisi O, Li B (2019) Least square support vector machine and multivariate adaptive regression splines for streamflow prediction in mountainous basin using hydro-meteorological data as inputs. Journal of hydrology, 580: 983-993

[2] Aggarwal SK, Goel A, Singh VP (2012) Stage and discharge forecasting by SVM and ANN techniques. Water ResourManag 26:3705–3724

[3] Asefa T, Kemblowski M, McKee M, Khalil A (2005) Multi-time scale stream flow predictions: The support vector machines approach. J. of Hydrology, 318 (1-4): 7-16.

[4] Barzegar R, Ghasri M, Qi Z, Quilty J, Adamowski J (2019) Using bootstrap ELM and LSSVM models to estimate river ice thickness in the Mackenzie River Basin in the Northwest Territories, Canada. Journal of Hydrology, 577:880-903

[5] Bhagwat PP, Maity R (2012) Multistep-ahead river flow prediction using LS-SVR at daily scale. J Water Resource Prot 4:528–539

[6] Buyukyildiz M, Kumcu SY (2017) An Estimation of the Suspended Sediment Load Using Adaptive Network Based Fuzzy Inference System, Support Vector Machine and Artificial Neural Network Models. Water Resources Management 31(2):1-17

[7] Dibike YB, Velickov S, Solomatine D, Abbott MB (2001) Model induction with support vector machines: introduction and applications. J Comput Civil Eng 15:208–216

[8] Duan QY, Sorooshian S, Gupta VK (1994) Optimal use of the SCEUA global optimization method for calibrating watershed models. J Hydrol 158:265–284

[9] Elkiran G, Nourani V, Abba SL (2019) Multi-step ahead modelling of river water quality parameters using ensemble artificial intelligence-based approach. Journal of Hydrology, 577:962-974

[10] Fathian F, Mehdizadeh S, KozekalaniSales A, Mir J, Safari S (2019) Hybrid models to improve the monthly river flow prediction: Integrating artificial intelligence and non-linear time series models. Journal of Hydrology, 575:1200-1213

[11] Ferreira C (2001) Gene expression programming: a new adaptive algorithm for solving problems. Complex Systems, Vol.13(2): 87–129.

[12] Ghazvinei T, ShamshirbandSh, MotamediSh, Hassanpour H, Salwana E (2017) Performance investigation of the dam intake physical hydraulic model using Support Vector Machine with a discrete wavelet transform algorithm. Computers and Electronics in Agriculture, 140:48-57

[13] Ghorbani MA, Khatibi R, Asadi H, Yousefi P (2012) Inter-Comparison of an Evolutionary Programming Model of Suspended Sediment Time-series whit other Local Model. INTECH.doi. org/10.5772/47801,. 255-282

[14] Ghorbani MA, KhatibiR,Goel A, FazeliFard MH, Azani A (2016) Modeling river discharge time series using support vector machine and artificial neural networks. Environ Earth Sci. DOI: 10.1007/s12665-016-5435-6

[15] Goel A, Pal M (2012) Stage–discharge modeling using support vector machines.IJE Trans A Basics. doi:10.5829/idosi.ije.2012.25. 01a.01

[16] Guven A (2009) Linear genetic programming for time-series modelling of daily flow rate. Journal Earth System Science, vol 118, 157-173.

[17] He Z, Wen X, Liu H, Du J (2014) A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. Journal of Hydrology, 509:379-386

[18] Imani M, Chao H, Lan W, Kuo C (2018) Daily sea level prediction at Chiayi coast, Taiwan using extreme learning machine and relevance vector machine. Global and Planetary Change, 161:211-221

[19] Jayawardena AW, Muttil N, Fernando TMKG (2005) Rainfall-Runoff ModellingusingGenetic Programming. International Congress on Modelling and Simulation Society of Australia and New Zealand December: 1841-1847..

[20] Karahan H, Iplikci S, Yasar M, Gurarslan G (2014) River Flow Estimation from Upstream Flow Records Using Support Vector Machines. Journal of Applied Mathematics.14(7):7-14

[21] Khatibi R, Naghipour L, Ghorbani MA, Aalami MT (2012) Predictability of relative humidity by two artificial intelligence techniques using noisy data from two Californian gauging stations. Neural computing and application: 643-941.

[22] Kisi O, Shiri J (2012) River suspended sediment estimation by climatic variables implication: Comparative study among soft computing techniques. Computers & Geosciences,43(4):73-82

[23] Kisi O, Cobaner M (2009) Modeling river stage–discharge relationships using different neural network computing techniques. Clean Soil Air Water 37:160–169

[24] Lin J, Cheng C, Chau K (2006) Using support vector machines for long-term discharge prediction. Hydrological Sciences Journal.51(4):599-610.

[25] Liong SY, Sivapragasam C (2002) Flood stage forecasting with support vector machines. J Am Water Resour 38:173–186

[26] Londhe S, Gavraskar S (2018) Stream Flow Forecasting using Least Square Support Vector Regression. Journal of Soft Computing in Civil Engineering , 2(4):56-88

[27] Misra D, Oommen T, Agarwal A, Mishra SK, Thompson AM (2009) Application and analysis of support vector machine based simulation for runoff and sediment yield. BiosystEng 103:527–535

[28] Moharrampour M, Mehrabi A, Katouzi M (2012) Daily Discharge Forecasting Using Support Vector Machine. International Journal of Information and Electronics Engineering.2(5):769-772

[29] Nourani V, Alizadeh A, Roushangar K (2016) Evaluation of a Two-Stage SVM and Spatial Statistics Methods for

Modeling Monthly River Suspended Sediment Load. Water Resources Management,30(1):393-407

[30] Rezaei M, Kim B, Fallah H, Alghmand S (2019) Daily river flow forecasting using ensemble empirical mode decomposition based heuristic regression models: Application on the perennial rivers in Iran and South Korea. Journal of Hydrology,572:470-485

[31] Sahoo BB, Jha R, Singh A, Kumar D (2019) Application of Support Vector Regression for Modeling Low Flow Time Series. Water Resources and Hydrologic Engineering, 23:923-934

[32] Shin S, Kyung D, Lee S, Taik& Kim J, Hyun J (2005) An application of support vector machines in bankruptcy prediction model. Expert Systems with Applications, 28: 127-135.

[33] Sivapragasam C, Muttil N (2005) Discharge rating curve extension a new approach. Water ResourManag 19:505–520

[34] Tongal H, Booij M (2018) Simulation and forecasting of streamflows using machine learning models coupled with base flow separation. Journal of Hydrology, 564:266-282

[35] Vapnik VN (1998) Statistical Learning Theory. Wiley, New York.

[36] Wang W, Men C, Lu W (2008) Online prediction model based on support vector machine. Neurocomputing 71:550–558

[37] Xu L, Wang J, Guan J, Huang F (2007) A Support Vector Machine Model for Mapping of Lake Water Quality from Remote-Sensed Images. IC-MED. Vol. 1(1), pp. 57-66.

[38] Yassen ZM, Awadh SM, Sharafati A, Shahid S (2018) Complementary data-intelligence model for river flow simulation. Journal of Hydrology, 567:190-190

[39] Yu PS, Chen ST, Chang IF (2006) Support vector regression for realtime flood stage forecasting. J Hydrol 328:704–716