Modeling and Optimization of Liqvan Rainfall–Runoff Using Genetic Algorithm and Moving Aggregation Method

S. Hashemi Kia, M. Hashemi kia, and A. Fakheri Fard

***Abstract*— Importance and significant role of rainfall-runoff process in water resource studies, has made it to be taken into attention by specialists from long time ago. Thus, many algorithms have been developed to model this process such as: genetic algorithm, dynamic and static artificial neural network, fuzzy and neuro-fuzzy systems and wavelet analysis in addition to regression methods. In this research genetic algorithm is used to model daily rainfall-runoff process in Liqvan catchment basin in an area of 7619 Km2. In the present study, input data were modeled as daily data. Then, the data were cumulated and modeled in 7, 10, 15, 20 and 30 day periods in order to make results more applicable. The results are indicative of error reduction in case of data accumulation for modeling input data and analysis of nonlinear phenomenon of river flow variations relative to rainfall.**

***Keywords*— Rainfall-Runoff, Genetic Algorithm, Modeling, Cumulated.**

I. Introduction

Rainfall-runoff process is a quite nonlinear phenomenon which is usually reflected in derived relations. This process has been one of the most important issues which have interested experts associated with water issues and especially hydrologists. Determining runoff caused by rainfall is not only important for flood forecasting but also can be used to recognize effects caused by considered changes in a catchment or generally it can be used in management of water resources. Since Sherman (1932) proposed unit hydrograph concept, a wide range of rainfall-runoff models are used to simulate mentioned process. Nonlinear property, inherent uncertainty of rainfall-runoff process, and requirement of vast and complex information, are some reasons that have encouraged scientists to use methods inspired by nature like genetic programming (GP). By most catchment basins of country being flood prone, expansion of water resource development projects in basins and computer technology advances, the need for flood management through modeling is significantly increased. Methods inspired by nature like genetic programming, are employed in sophisticated and accurate investigations. Genetic programming is an automated programming technique which is based on Darwin's evolutionary theory and is able to model nonlinear processes. Advantage of GP compared to other models such as artificial neural network is that in GP, blocks construction (input variables, objective, and total functions) are defined initially and then the optimized construction of model and coefficients are obtained during learning process. Also, GP is able to automatically select the variables which are most effective in model, and this is while in other methods this feature is not possible. Wigham and Kroper (2001) modeled rainfall-runoff process in Tiffei and Namei catchment basins using genetic programming and Ihackers deterministic model. Results obtained from genetic programming were more accurate than deterministic model. Khou et al (2001) took advantage of genetic programming to predict hourly runoff in a research on Orgowal catchment basin in France, and compared obtained results with observed values and also calculated values from classic methods. Result of study showed acceptable accuracy of genetic programming. Lee Young et al (2002) by studying rainfall-runoff relation in different moments, found that using genetic programming in prediction of rainfall-runoff behavior in catchment basins results in fewer errors. Jayawardena et al (2005) modeled rainfall-runoff process in two relatively large catchments in China by daily data using genetic programming. Obtained results from __ exhibited a suitable compliance with actual data. Aytek and Kisi (2008) modeled sediments transport phenomenon of Tango and Montana rivers by daily data using genetic programming and results from GP were well matched with sediments intensity graphs and multiline regression models. Aytek et al (2008) used neural networks and genetic programming to model daily rainfall-runoff of Juniata river catchment basin in Pennsylvania/America, and they concluded that genetic programming models rainfall-runoff process more accurately than artificial neural networks. Ostorikar and Deo (2008) by employing a genetic program to estimate incomplete data of wave heights in Gulf of Mexico, found that this method leads to a desirable accuracy in estimation of data associated with time series.

Therefore according to preceding points, purpose of present study is application of genetic programming in estimation of rainfall-runoff process in two strategies of daily estimation and moving aggregation in periods of 7, 10, 15, 20, and 30 days conducted in Liqvan catchment basin which is one of sub-basins of Urmia Lake. In the present study, 20% of data are used for verification and 80% of data are used for training in software.

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II. Materials and Methods

2-1- The Region of Study

Case study of this investigation is Liqvan Chay River, which is one of the rivers of Aji Chay catchment basin in Eastern Azerbaijan, Iran, and consists two Liqvan and Heravi stations. Liqvan Chay basin is located in an area of 75 Km2 on the northern hillside of Sahand mountain between eastern longitudes of and northern latitude of and . According to topography of the region, the basin has a relatively uniform slope. Liqvqn River is 14 Km long, and is fed by flows from snowmelts, rainfalls and fountains. River's main drainage includes Liqvan River and its main sub-branches including Baraleh Chay, Bozkesh Chay, and Baqchedareh which are finally drained to it before hydrometric station. In the present research daily data of Liqvan station are used from the date of 1/7/1346 up to 31/6/1391. Table.1 indicates stochastic properties of these data, and Fig.1 shows Liqvan Chay catchment basin.

TABLE I: STOCHASTIC PROPERTIES OF RAINFALL-RUNOFF VALUES USED IN INTERVAL OF 1/7/1346 TO 31/6/1391

The statistical parameters	Discharge (m^3/s)						Precipitation (mm/day)					
	All data	7day cumulative data	10day cumulative data	15day cumulative data	20day cumulative data	30day cumulative data	All data	7day cumulative data	10day cumulative data	15day cumulative data	20day cumulative data	30day cumulative data
Number	8767	8760	8757	8752	8747	8737	8767	8760	8757	8752	8747	8737
Mean	13.262	5.72	8.173	12.263	16.356	24.55	0.114	6.33	9.05	13.574	18.1	27.13
Skewness	5.454	2.667	2.633	2.593	2.56	2.488	4.512	2.288	2.633	1.68	1.505	1.301
Maximum	57	50.7	66.74	99.23	127.2	186.7	2.28	77.5	66.74	109.5	124.8	144.1
Minimum	0	0.19	0.29	0.435	0.58	1.438	0	0	8.172	0	0	0

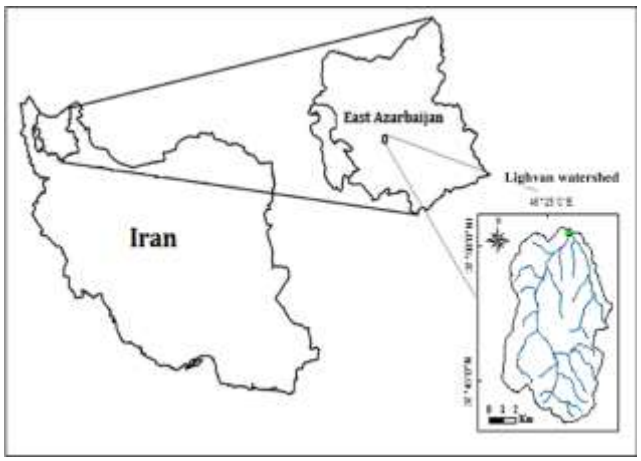

Fig. 1. Liqvan catchment basin location

2-2- Genetic Algorithm (GA)

Genetic programming is generalized form of genetic algorithm which was at first presented based on Darwin's Evolution theory. In the way that a population in evolution leaves improper members and generates modified children. In the beginning of the process of this method no functional relation is considered, and this method is able to optimize model construction and its components. Genetic programming unlike genetic algorithm, performs on tree structure of formulas instead of a series of binary digits. Tree construction is made of a set of functions (mathematical operators used in formulas), and terminals (problem variables and constant numbers), (Koza 1992).

Before operational steps of genetic programming, following primary steps must be determined by user:

1. Terminal aggregations (problem variables, random constant numbers), 2. Mathematical operator's aggregation used in formulas, 3. Fitting function selection to examine formulas fitting, 4. Controller parameters determination of implementation of (population size, probability associated with employing genetic operations, and other details related to program performance), 5. Finalizing and result presenting criteria of the program (like, new generation population size, determining of a certain value for formulas fitting to stop operation in the case in which fitted value is equal or more than the determined value) genetic programming operational process is as following steps:

1. Generating an initial population of formulas which are produced by random combination of a set of functions (mathematical operators used in formulas) and terminals (problem variables and constant numbers).

2. All members of the mentioned population are evaluated by fitting functions.

3. Generating a new population of formulas; following steps are used to generate a new population:

3.1) One of the genetic operations is chosen from crossover, mutation and inheritance (these three genetic operations are the most important operations used in genetic programming. Other operations like construction modification and … are used with lower probability)

3.2) Proper number of available population members are chosen (selection of population members are probabilistic, and in this probable selection members with better fittings are preferred to the members with worse fittings, and this fact does not mean that members with worse fittings are definitely removed).

3.3) Chosen genetic operation is used to generate new children (new formula).

3.4) Generated child (new formula) is entered in a population.

3.5) Considered model is evaluated using fitting function. Executive steps outline of genetic programming is illustrated in Fig.2.

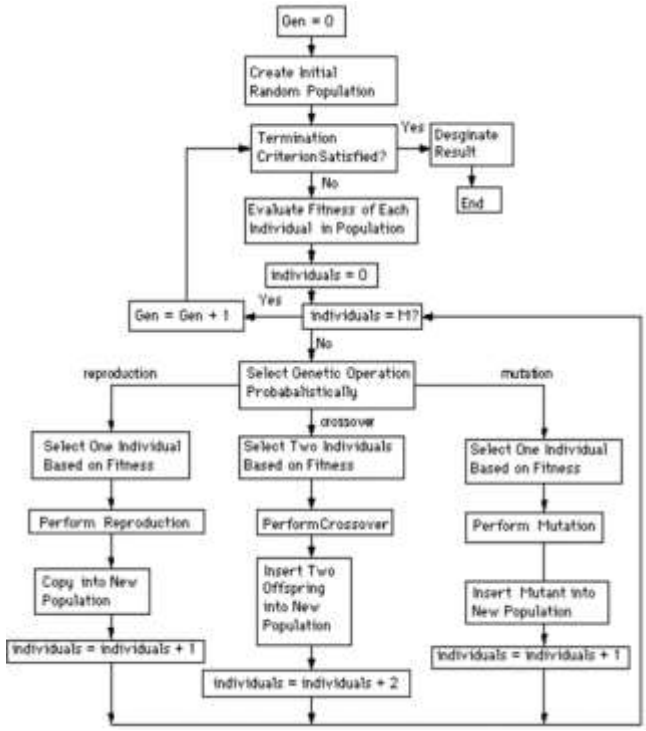

Fig. 2. Executive steps outline of genetic programming

The state relation in GP is generally as follows:

$$Q_{t+\delta\Delta t} = f\left(R_t, R_{t-\Delta t}, \dots, R_{t-\Delta Wt}, Q_t, Q_{t-\Delta t}, \dots, Q_{t-W\Delta t}\right) \quad (1)$$

Where Q is runoff in $m^3 s^{-1}$, R is rainfall intensity in $mmday^{-1}$, δ ($\delta = 1,2,\dots$) is a parameter which shows how far runoff estimation is desirable. W parameter (W=1, 2…) shows how far runoff and rainfall data are effective on runoff estimation with time intervals of Δt.

Models with $M_a P_b Q_c$ format are shown, where M shows model, a shows model type (daily, 7 or 10 days moving aggregation), P shows rainfall and b shows the number of rainfall imposed in the model (the rainfall delay numbers along with the rainfall on the same day), Q shows runoff, and *c* shows number of runoffs imposed in the model (the number of runoff delays).

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2-3- Error and Accuracy Examination Parameters in order to Compare Different Methods

Performance of models used in this investigation is evaluated according to root mean square error (RMSE) and correlation coefficient (R^2) which are calculated respectively using Eq.1 and Eq.2.

$$R^2 = 1 - \frac{\sum(Q_t - Q_o)^2}{\sum(Q_t - Q_o)} \quad (1)$$

$$RMSE = \sqrt{\frac{(Q_t - Q_o)^2}{N}} \quad (2)$$

In the equations above, R^2 is correlation coefficient, RMSE is root mean square error, Q_o and Q_t are observed and calculated values respectively in *i* time step, N is number of time steps, Q_o and Q_t are also average of observed and calculated values respectively. In addition to the preceding criteria, observing-calculating diagrams were also used in order to evaluate models.

III. Results and Discussion

Modeling and estimating of a river flow is one of the important and significant components in scheduling, designing and management of water resources. In the present study, genetic programming method is used to estimate amount of flow in one or multiple days in Liqvan catchment basin in Liqvan station.

Data used in the present study include amounts of rainfall and river flow rate in a stochastic period of 8767 days in different combinations. In this research, 6 variables Q_{t-1}, Q_{t-2}, Q_{t-3}, P_t, P_{t-1}, P_{t-2}, and Pt_{-3} from previous runoff and rain pulses, were used to determine river flow. In the beginning of calculations, data were inserted into the genetic programming daily. Table.2 illustrates daily data in $M_1P_4Q_2$ model with mean square error of 0.2383 and correlation coefficient of 0.9297 in training data and mean square of 0.3085 and correlation coefficient of 0.9288 are known as the best model in the test.

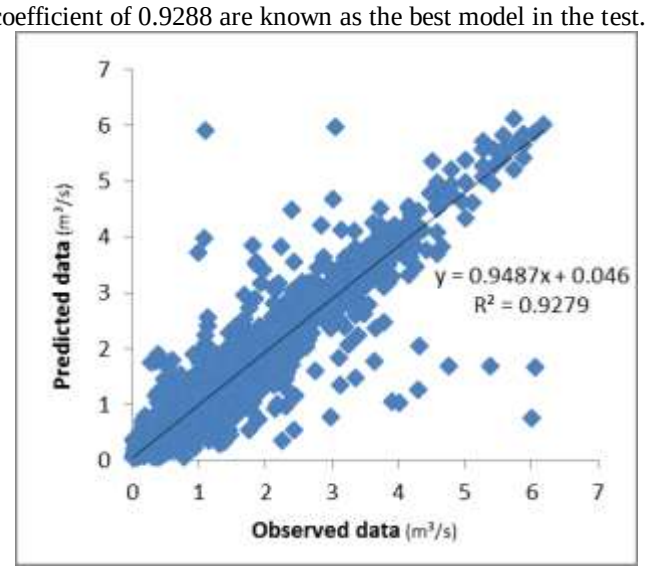

Fig. 3. Comparison of observed and calculated values of $M_1P_4Q_2$ model

TABLE II: RESULTS OF DAILY DATA MODELING USING GENETIC ALGORITHM

Models	Input data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_1P_1Q_0$	P_t	0.0176	0.877	0.0326	1.138
$M_1P_2Q_0$	P_t , P_{t-1}	0.0238	0.8742	0.041	1.1312
$M_1P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.02687	0.8728	0.0271	1.1366
$M_1P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.035	0.8691	0.06238	1.1208
$M_1P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9281	0.8932	0.9292	0.3097
$M_1P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9297	0.2383	0.9288	0.3085
$M_1P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P_t$, $P_{t-1}P_{t-2}P_{t-3}$	0.9297	0.2355	0.8967	0.3709

Fig. 3 indicative of acceptable and realistic modeling in $M_1P_4Q_2$ model.

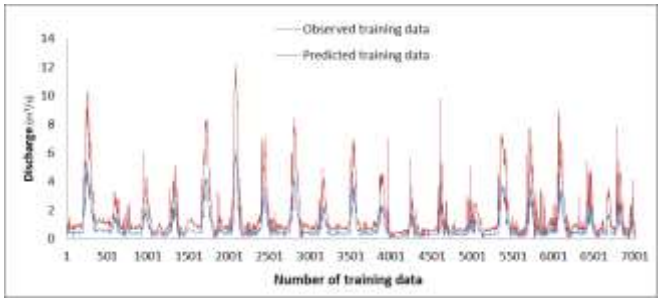

Fig. 4. The observing and estimating river flow or using genetic programming modeling for the $M_1P_4Q_2$ model

Then, for more extended usage and partial error reduction, data were inserted into the genetic programing system in 7, 10, 15, 20, and 30 days cumulatively. As an example, runoff data for 30 days aggregative model are shown in Eq.3 and also rainfall data for 10 days aggregative model are calculated as in Eq.4.

$$\begin{cases} Q_{30:1} = Q_1 + Q_2 + \cdots + Q_{29} + Q_{30} \\ Q_{30:2} = Q_2 + Q_3 + \cdots + Q_{30} + Q_{31} \\ \vdots \\ Q_{30:n} = Q_{n-29} + Q_{n-28} + \cdots + Q_{n-1} + Q_n \end{cases} \quad (3)$$

$$\begin{cases} P_{10:1} = P_1 + P_2 + \cdots + P_9 + P_{10} \\ P_{10:2} = P_2 + P_3 + \cdots + P_{10} + P_{11} \\ \vdots \\ P_{10:n} = P_{n-9} + P_{n-8} + \cdots + P_{n-1} + P_n \end{cases} \quad (4)$$

To examine accuracy of each mentioned methods, various combinations of rainfall and flow rate values were made like daily modeling, and were used as the inputs of these models. Table.3 shows values associated with each one of indexes in training and test period for flow rate and also for 7 days aggregative data. According to the acceptable accuracy of the $M_7P_4Q_2$ model, it's concluded that input variables of this method are the most meaningful variables for the rainfall-runoff process modeling of catchment basin for cumulative data of the mentioned station in 7 days.

TABLE III: ACCURACY STOCASTIC VALUES OF MODELS OBTAINED IN 7 DAYS

Models	Input data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_7P_1Q_0$	P_t	0.04586	5.8765	0.7218	7.4941
$M_7P_2Q_0$	P_t , P_{t-1}	0.04622	5.8751	0.8114	7.4674
$M_7P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.04966	5.8686	0.081	7.4449
$M_7P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.053	5.8549	0.1028	7.4076
$M_7P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9949	0.4279	0.99133	0.727
$M_7P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9973	0.3113	0.99596	0.5239
$M_7P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P_t$, $P_{t-1}P_{t-2}P_{t-3}$	0.99727	0.3142	0.9954	0.5251

Fig. 5 shows appropriate matching of the observed and calculated data according to the $M_7P_4Q_2$ model.

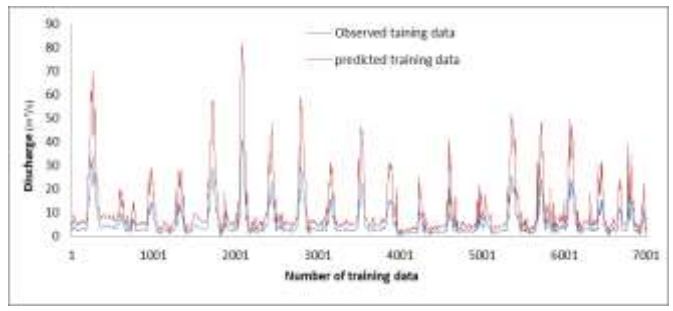

Fig. 2. Observed and estimated values of river flow using genetic programming model for $M_7P_4Q_2$ model

In Fig.6 observed and calculated data are plotted together which indicates a high correlation coefficient with the value of 0.9973 in $M_7P_4Q_2$ model.

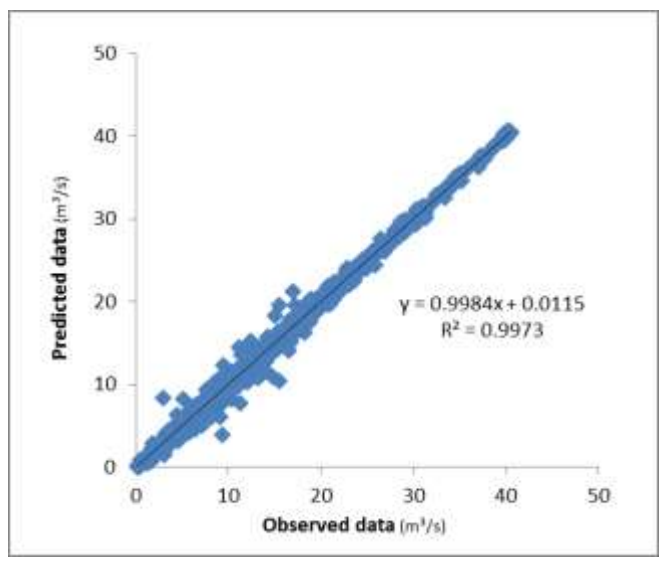

Fig. 6. comparison of observed and calculated values of $M_7P_4Q_2$ model

By comparing results of different states with considering various inputs for cumulative data of 10 days for each one of them in Table 4, $M_{10}P_4Q_3$ model was selected as the best model with root mean square error of 0.31235 and correlation coefficient of 0.998635 for training data, and with root mean square error of 0.5058 and correlation coefficient of 0.9978 for test data

TABLE IV: ACCURACY STOCASTIC VALUES OF MODELS OBTAINED IN 10 DAYS

Models	Input Data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_{10}P_1Q_0$	P_t	0.05438	8.2953	0.09718	10.4379
$M_{10}P_2Q_0$	P_t , P_{t-1}	0.0591	8.2756	0.08074	10.5098
$M_{10}P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.06116	8.2715	0.11051	10.4252
$M_{10}P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.06738	8.2394	0.121045	10.325
$M_{10}P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.99695	0.47196	0.9948	0.787
$M_{10}P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.998636	0.3155	0.99746	0.55077
$M_{10}P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P$, ,$P_{t-1}P_{t-2}P_{t-3}$	0.99865	0.31235	0.9978	0.5058

Fig.7 and Fig.8 illustrate the observed and calculated data for $M_{10}P_4Q_3$ model.

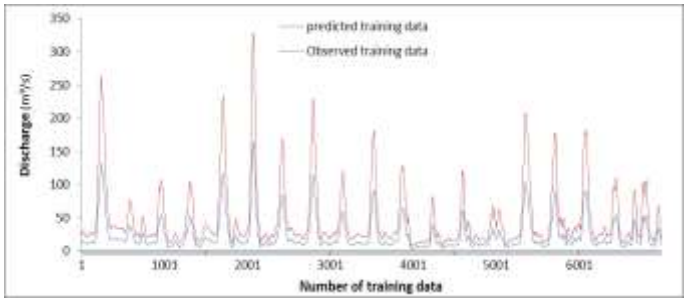

Fig. 3. The observed and estimated river flow using genetic programming model for the $M_{10}P_4Q_3$ model

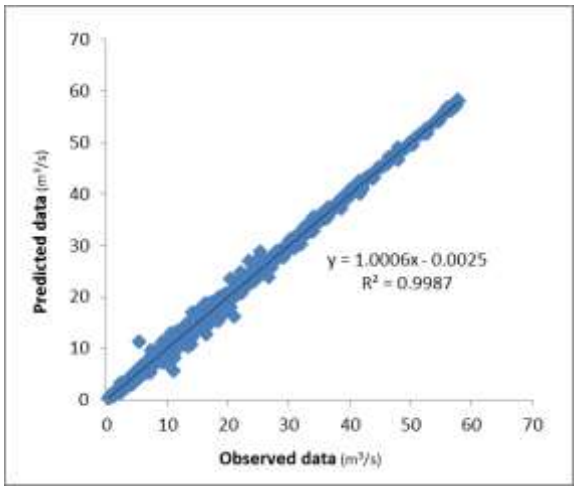

Fig. 4. comparison of observed and calculated data of $M_{10}P_4Q_3$ model

Table.5 shows values associated with each criteria in training and testing period for flow rate, for cumulative data of 15 days. According to the acceptable accuracy of $M_{15}P_4Q_3$ model, it can be concluded that input variables of this model are most meaningful variables for the rainfall-runoff modeling in catchment basin for cumulative data of 7 days in the mentioned station.

TABLE V: STOCASTICVALUES OF ACCURACY OF MODELS OBTAINED IN 15 DAYS

Models	Input data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_{15}P_1Q_0$	P_t	0.0675	12.2200	0.1118	15.3900
$M_{15}P_2Q_0$	P_t , P_{t-1}	0.0706	12.2050	0.1280	15.1254
$M_{15}P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.0774	12.1612	0.1358	15.0850
$M_{15}P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.0823	12.1290	0.1460	15.0260
$M_{15}P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9982	0.5383	0.9971	0.8655
$M_{15}P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9994	0.3230	0.9986	0.5885
$M_{15}P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P$, ,$P_{t-1}P_{t-2}P_{t-3}$	0.9994	0.3180	0.9988	0.5306

Fig.9 and Fig.10 show observed and calculated data for $M_{15}P_4Q_3$ model.

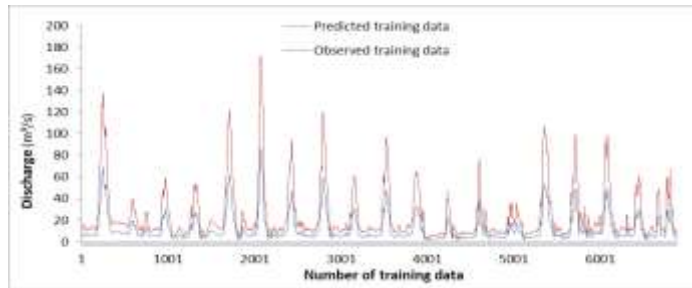

Fig. 5. observed and estimated values of river flow using genetic programming model for $M_{15}P_4Q_3$ model

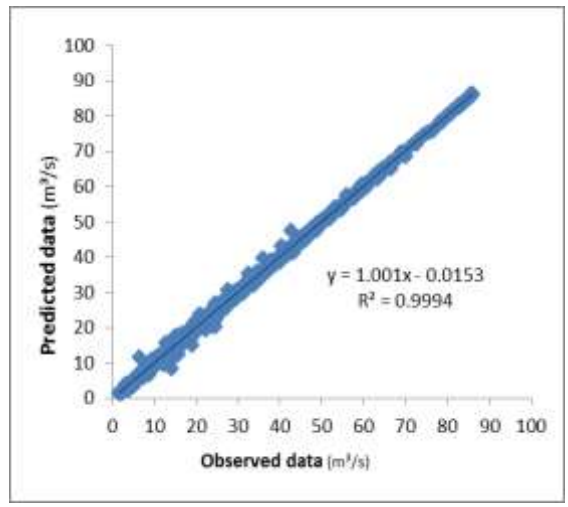

Fig. 6. comparison of calculated and observed values of the $M_{15}P_4Q_3$ model

By comparing results of different states with considering various inputs for cumulative data of 20 days for each one of them in Table 6, $M_{20}P_4Q_2$ model is selected as the best model with root mean square error of 0.332 and correlation coefficient of 0.99960 for training data, and with root mean square error of 0.4095 and correlation coefficient of 0.99962 for test data.

TABLE VI : STOCASTIC VALUES OF ACCURACY OF MODELS OBTAINED IN 20 DAYS

Models	Input data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_{20}P_1Q_0$	P_t	0.07522	16.067	0.1465	19.7058
$M_{20}P_2Q_0$	P_t , P_{t-1}	0.08644	15.978	0.1439	19.7812
$M_{20}P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.08722	15.962	0.1605	19.5953
$M_{20}P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.098096	15.87	0.1721	19.48
$M_{20}P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9986	0.62439	0.996	0.9757
$M_{20}P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.9996075	0.332	0.999627	0.4095
$M_{20}P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P$, ,$P_{t-1}P_{t-2}P_{t-3}$	0.9996076	0.331	0.999624	0.41

Fig.11 and Fig.12 indicate observed and calculated data for $M_{20}P_4Q_2$ model.

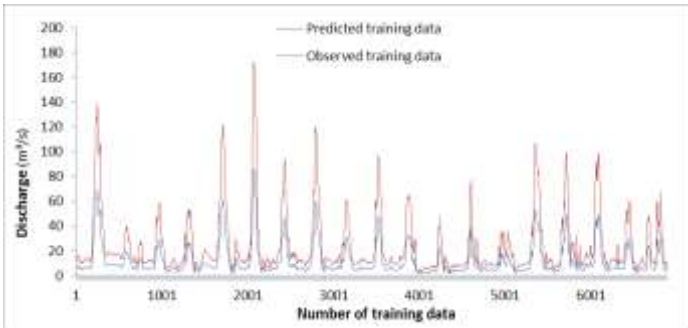

Fig. 7. observed and estimated values of river flow using genetic programming model for the $M_{20}P_4Q_2$ model

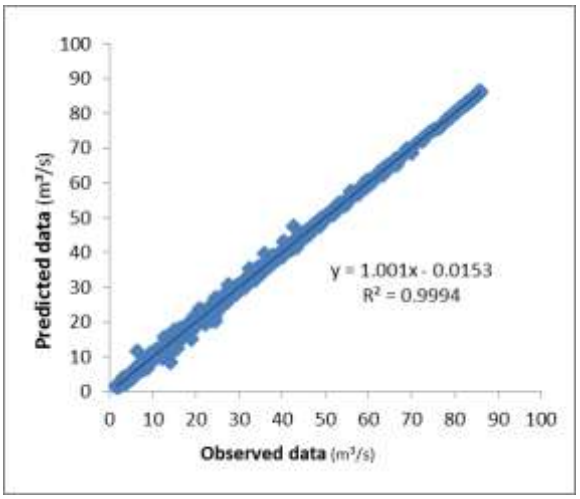

Fig. 8. comparison of calculated and observed values of $M_{20}P_4Q_2$ model

Table.7 shows values associated with each criteria in training and testing period for flow rate, for cumulative data of 30 days. According to the acceptable accuracy of $M_{30}P_4Q_3$ model, it can be concluded that input variables of this model are the most meaningful variables for the rainfall-runoff modeling in the catchment basin for cumulative data of 7 days in mentioned station.

TABLE VII: STOCASTIC VALUES OF ACCURACY OF MODELS OBTAINED IN 30 DAYS

Models	Input data	Training		Test	
		R^2	RMSE	R^2	RMSE
$M_{30}P_1Q_0$	P_t	0.09438	23.3127	0.18805	27.9995
$M_{30}P_2Q_0$	P_t , P_{t-1}	0.105027	23.1842	0.19518	27.82
$M_{30}P_3Q_0$	P_t, P_{t-1}, P_{t-2}	0.112264	23.0798	0.18821	28.118
$M_{30}P_4Q_0$	P_t , P_{t-1}, P_{t-2}, P_{t-3}	0.119746	22.993	0.2272246	27.358
$M_{30}P_4Q_1$	Q_{t-1}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.99907	0.74904	0.9986	1.1667
$M_{30}P_4Q_2$	Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{t-3}	0.999813	0.33524	0.9997	0.4438
$M_{30}P_4Q_3$	$Q_{t-1}Q_{t-2}Q_{t-3}P_{,t}P_{t-1}P_{t-2}P_{t-3}$	0.999813	0.335	0.99979	0.4329

Fig.13 and Fig.14 indicate observed and calculated data for $M_{30}P_4Q_3$ model

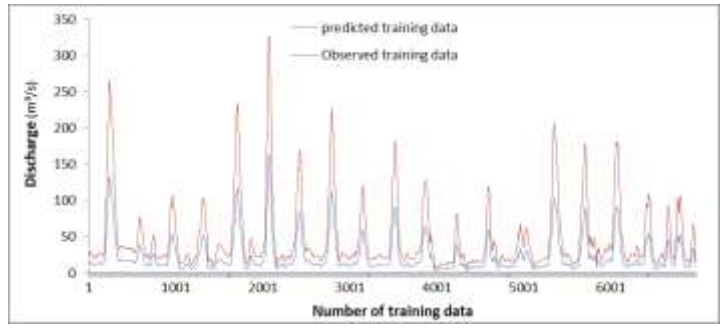

Fig. 9. observed and estimated values of river flow using genetic programming model for the M30P4Q3 model

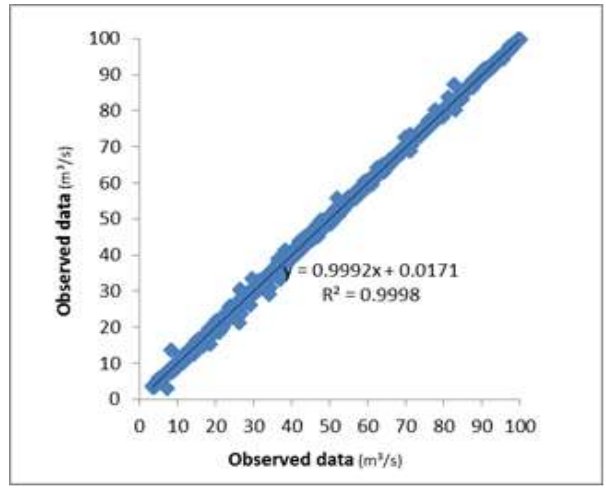

Fig. 10. comparison of calculated and observed values of THE $M_{30}P_4Q_3$ model

IV. CONCLUSION

According to the fact that rainfall-runoff phenomena is nonlinear, this phenomena have to be modeled by using nonlinear methods like genetic programing.

In this research using rainfall-runoff data cumulating of 7, 10, 15, 20, and 30 days, and also comparing them with the ordinary daily modeling, it was clarified that rainfall-runoff data cumulating leads to the elimination of short term noises, and thus it causes R^2 to increase, and also, a modification factor can be applied on the obtained models to reduce absolute error.

One of the other applications of cumulating method is to determine capacity of reservoirs, especially farm reservoirs in time periods of 7 to 30 days.

In Fig.9 it can be understood that mean square error value is minimum in $M_{10}P_4Q_3$ model with maximum data aggregation. This model also have the maximum correlation coefficient among others, and according to our research results, we can use cumulating method or moving analysis method to predict irrigating period and calculate amount of required irrigation for plants which is not satisfied by effective rainfall.

Obtained results can be used to determine irrigation periods in farms and they also can be used in rainfed analysis to specify rainfed lands.

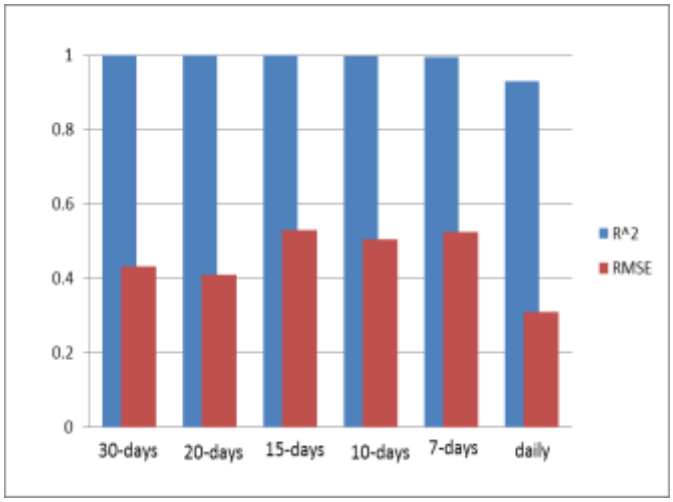

Fig. 11. comparison of correlation coefficent value and RMSE between the best selected models

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