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A New Fuzzy Modeling Method for the Runoff Simulation in the Karoon Basin

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Abstract: Fuzzy concepts and related inferences have been proposed a new approach to human modeling and calculation methods. Although, different powerful fuzzy modeling methods have been developed up to now, but some of these methods are different with real human modeling method, because of utilized mathematics and exact calculations in their constructions. Active Learning Method (ALM) is a fuzzy modeling method which uses a very basic level of mathematics. ALM has been innovated in 1997 and a new modified ALM developed in 2007. ALM has very simple algorithm that avoids of mathematical complexities. In this study, novel modified ALM has been utilized for the simulation of daily runoff in Karoon basin (one of the most important basins in Iran). Hence, the daily discharge data of Karoon River in Pol-e-Shaloo station from 1991 until 1999 were gathered for modeling. The first five years (1991-1995) were used for the training of ALM model and the residual data were used for the test of trained model. The impacts of changing the fuzzification points on the simulation results were investigated and the results showed that ALM for simulation of daily runoff is not sensitive to the position of fuzzy dividing points and best positions were determined. At the first step of modeling, the input data used for ALM modeling were daily precipitation, temperature, humidity and vapor pressure with different time lags. In this study, several statistical (The Nash-Sutcliffe, R^2, Bias, Root mean square error (RMSE), peak weighted RMSE (PWRMSE) and Percent of total volume error (PTVE) values) and graphical (hydrograph, scatter plot and quantile-quantile) criteria were used for the evaluation of the ALM modeling results. NS, R^2, Bias, RMSE, PWRMSE and PTVE of the tested ALM model with 32 fuzzy rules for daily runoff modeling were 0.29, 0.33, 65.8 (cms), 265.4 (cms), 418.9 (cms) and 22.3%, respectively. In general, the results of daily runoff simulation were not so good. Hence, in the next step of modeling, the daily discharges with different lags were added to the previous input dataset. The results showed that ALM with 32 rules is the best model for runoff simulation. NS, R^2, Bias, RMSE, PWRMSE and PTVE of the tested ALM model with 32 fuzzy rules for daily runoff modeling were 0.75, 0.75, 1.3 (cms), 157 (cms), 357 (cms) and 0.5%, respectively. These excellent results demonstrated the effect of adding discharge data to input dataset and showed the ALM ability for daily runoff simulation. ALM could identify and rank the important variables for runoff simulation and determined that temperature and vapor pressure are unnecessary variables. In addition, training of ALM is very easy and straightforward in comparison with other artificial intelligence methods such as ANN (Artificial Neural Networks) and ANFIS (Adaptive Neuro-Fuzzy Inference Systems). Therefore, according to the ALM abilities, it has merit to be introduced as a novel and appropriate modeling method for the runoff simulation.

Key words: Karoon river · Fuzzy modeling · Active learning method · Runoff simulation

INTRODUCTION

Runoff simulation is a very important subject for engineers and hydrologists. Estimation of river flow can have a significant economic impact, as it can help in agricultural water management, water shortages management, water resources management and flood and drought prediction and management. Models can lead us to simulate the precipitation-runoff process and forecast the stream flows. Many techniques are currently

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used for modeling of hydrological process and generating of synthetic stream flow. One of these techniques is physically based conceptual modeling methods which are specially designed to mathematically simulate the sub processes and physical mechanisms which are related to hydrological cycle. These models usually incorporate simplified forms of physical deterministic laws that are representative of watershed characteristics that play a role in these [1]. For a case which has insufficient or no measured data of watershed characteristics, data-driven models are usually used to obtain the flow data [2]. These models are more useful since they can be applied easily and avoid of conceptual models complexities. Most frequently used of these models are regression models, time series models, artificial neural network (ANN) and fuzzy logic (FL). ANN is one of the most frequently used methods in the last fifteen years. This method is quite suitable for non-linear systems. Many researchers have utilized of ANN for prediction of stream flow [1-15].

Early information on principles of fuzzy logic was suggested by [16] and although it was thought in the beginning that it did not comply with scientific principles, it demonstrated itself by an application made by [17]. Fuzzy logic system can model human's knowledge qualitatively and avoid of delicate and quantitative analyses. Today it almost can be applied to the all of the engineering fields. Several studies have been carried out using fuzzy logic in hydrology and water resources planning [18, 19, 11, 21, 22] suggested a new fuzzy modeling technique similar to the human modeling method, which not only uses basic mathematics, but can also be implemented by biological neural networks. This method, entitled the active learning method (ALM), has a simple algorithm and avoids mathematical complexities and its accuracy increases by increasing the number of iterations [23] developed new heuristic search, fuzzification and defuzzification methods for ALM algorithm and a novel modified ALM was generated, which will be utilized in this study.

Up to now, no research has been performed using the ALM on the stream flow modeling, hence the ALM is used for stream flow modeling in this study and its performance is evaluated.

MATERIALS AND METHODOS

Case Study: The Karoon III basin (subbasin of large Karoon) is located in the southwest of Iran and that is one of the most important subbasins of Persian Gulf basin. The watershed boundaries are 49°,30' to 52° E and 30° to 32°, 30' N and its area is approximately 24200 km^2 with 30 reliable climatology and synoptic gauges. The elevation varies from 700m at the Pol-e-Shaloo hydrometric station (outlet of the Karoon III basin and upstream of Karoon III dam) to 4500m on Kouhrang and Dena Mountains. Digital elevation model (DEM) and major drainage system of basin is shown in Figure 1. About 50% of the watershed area has higher elevation than 2500m. The watershed receives an average annual precipitation of 767 mm that about 55% of precipitation is as snowfall. The average daily discharge flow of Karoon III basin is about 384 m^3/sec.

Algorithm of Active Learning Method: Here, ALM algorithm is described briefly. For details about ALM algorithm refer to [24, 25]. The different steps of ALM algorithm has been presented in Figure 2. Step 1. The input-output data of the studied system are gathered.

Step 2: The gathered data are projected on the x–y planes and for each variable a x-y plane is drawn. Figures 3a and 3b shows the data of a dummy two variables problem, projected on x_1-y and x_2-y planes, respectively.

Step 3: The Ink Drop Spread (IDS) operator is used to find continuous paths (general behaviors or implicit non-linear functions) on each x–y plane. IDS is a fuzzy interpolator. In IDS method, each data point in each plane is assumed to be a light source with a cone-shaped illumination pattern. As the distance from these light sources increases, their illumination patterns interfere and new bright areas are formed. Figures 3c and 3d show the results of application of the IDS method on Figures 3a and 3b, respectively. By applying the centre of gravity method on Figures 3c and 3d continuous paths are extracted (Figures 3e and 3f). These paths are one-variable nonlinear implicit functions.

Step 4: Subsequently, the deviation of data points around each continuous path (error of each continuous path) can be calculated by various methods such as the coefficient of determination (R^2), the root mean square error (RMSE) or the mean percent of absolute error (MPAE).

Step 5: The path with smaller deviation or error is selected according to the deviation or error, calculated in step 4 and then it is saved.

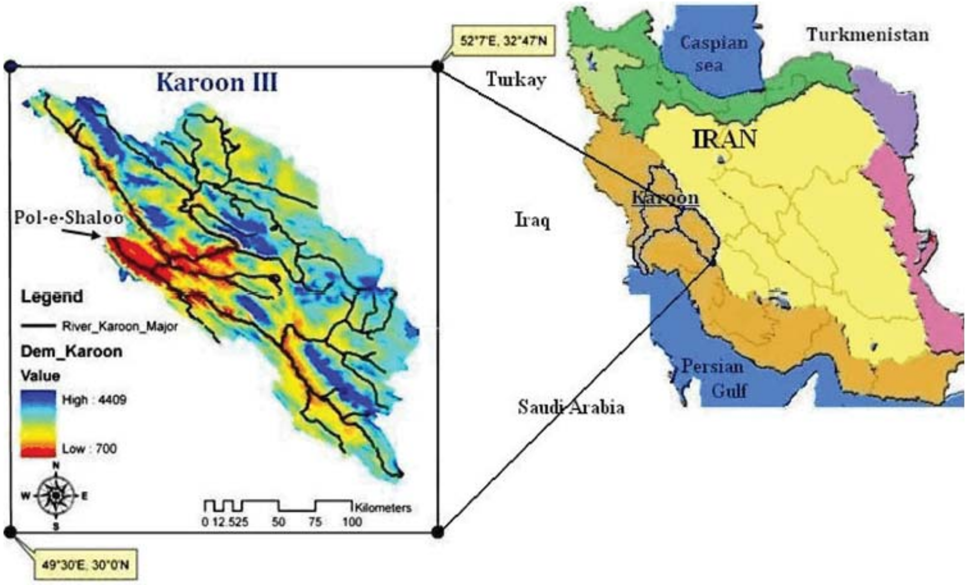

Fig. 1: DEM & major drainage network of Karoon III basin (subbasin of large Karoon)

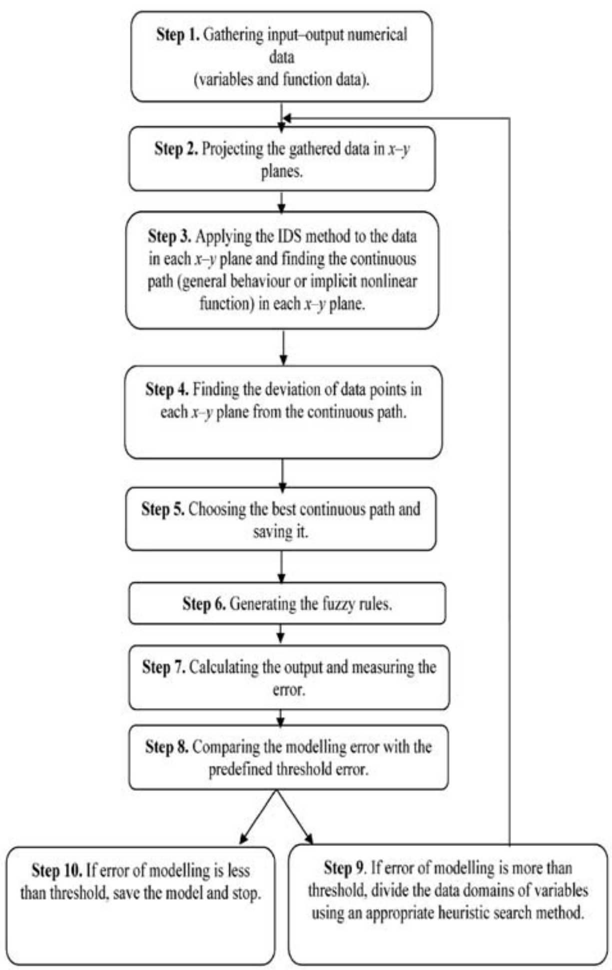

Fig. 2: Proposed algorithm for Active Learning Method

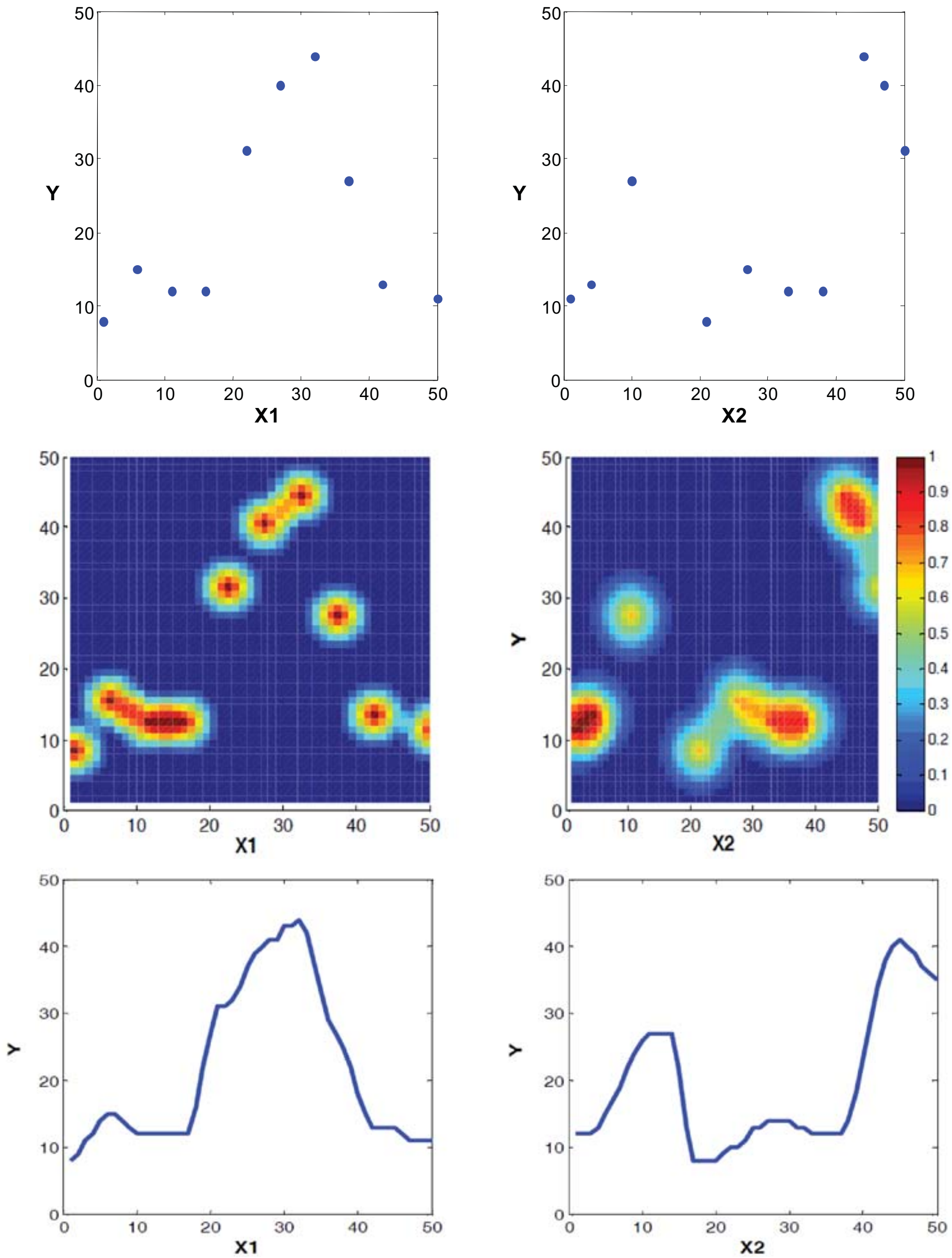

Fig. 3: (a) Projected data on x_1–y plane, (b) projected data on x_2–y plane, (c) results of applying the IDS method to the data points in the x_1–y plane, (d) results of applying the IDS to the data points in the x_2–y plane, (e) extracted continuous path by applying centre of gravity method on figure 3c and (f) extracted continuous path by applying centre of gravity method to figure 3d

Step 6: In the first iteration of algorithm the system can be modeled using the only one path, saved in the step 5. Hence, there is only one rule. After the next iterations of ALM algorithm, the space of variables is divided to some subspaces and number of rules in the generated fuzzy rule base is equal to the number of subspaces. Since the new heuristic search method, used in Step 9 is a complicated fuzzy dividing method that typical fuzzification methods are not compatible with it, therefore, a new simple fuzzy modeling method (fuzzification and defuzzification), developed by [23] was utilized, which is attuned to the developed heuristic search method. For detail about this new fuzzy modeling in the ALM algorithm see [23, 24].

Step 7: The error of modeling is calculated using the generated fuzzy rules.

Step 8: If the error of modeling is more than predefined error, then the Step 9 is performed, else the step 10 is activated and the procedure of ALM modeling is stopped.

Step 9: Using a heuristic search method, the space of variables should be partitioned to some subspaces fuzzily and then ALM procedure should be iterated from step 2 for each subspace independently. Fuzzy partitioning of multi-dimensional space is a combinatorial problem. There is no theoretical approach for it; therefore, heuristic search methods are used [26]. The heuristic search is a guided search and it does not guarantee an optimal solution. However, it can often find satisfactory solutions [27]. [23] developed a new heuristic search method for fuzzy dividing of space in the ALM algorithm. In this heuristic search method, the global error decreases simultaneously by decreasing the local errors. Here, this novel heuristic method is utilized.

Runoff Simulations by ALM and Evaluation Criteria: In this study, ALM has been utilized for the simulation of daily runoff in Karoon III basin. The Precipitation, temperature, humidity, vapor pressure and daily discharge data of Karoon River in Pol-e-Shaloo station from 23 Sep 1991 to 22 Sep 1999 were utilized for modeling. The first five years (23 Sep 1991 to 22 Sep 1996) were used for the training of ALM model and the residual data were used for the test of trained model. In spite of many other modeling methods (e.g. ANNs), the ALM does not need initial parameters to start the training and thus it does not repeat the training, hence ALM training is very easy and straightforward and it is not time consuming [24]. When we divide the domain of a variable fuzzily, then some of the data can be shared in small and big parts of the variable domain. The percent of common data in the small and big parts is related to the fuzzy dividing points. The fuzzy systems are not too sensitive to the dividing points. Therefore, the appropriate points for fuzzy dividing can be calculated by investigating various alternatives to select the most appropriate one [28, 24] showed that the first and third quarters of data are best dividing points. At the first stage, ALM is applied to the total datasets (precipitation, temperature, humidity, vapor pressure and discharge data) and the appropriate points for fuzzy dividing were determined. Then, daily precipitation, temperature, humidity and vapor pressure with the different time lags were used for ALM modeling and consequently, runoff simulation. It seems that the appropriate correlation exists between discharge data with different time lags. Therefore, effect of adding discharge data to input dataset was investigated. Variety of statistical (mean percent of absolute error (MPAE), coefficient of determination (R^2), mean bias, Nash-Sutcliffe efficiency (NS), root mean square error (RMSE), percent of total volume error (PTVE) and peak-weighted root mean square error (PW-RMSE)) and graphical goodness of fit criteria (Quantile-Quantile (Q-Q) Diagram, scatter plot and hydrographs) were used for the comprehensive evaluation of the modeling results.

RESULTS AND DISCUSSION

Appropriate Fuzzy Points Determination: For determination of appropriate fuzzy points, ALM modeling was performed with some dividing alternatives (20%, 40%, 50%, 60% and 80% of data are common in the small and big parts) using daily precipitation, temperature, humidity, vapor pressure and discharge with different time lags as input data. The results of ALM modeling have been exhibited in Figure 4. This figure shows that ALM is not so sensitive to the location of fuzzy points and the NS values show that model efficiency for different states from 40% to 80% are almost equal, hence the first and third quarters of data were selected as fuzzy dividing points and utilized in this study.

Runoff Simulation Without Discharge Data: The daily precipitation, temperature, humidity and vapor pressure data with four time lags were used as input data for ALM modeling (without discharge data as input variable). The model output was discharge values of Karoon River in the Pol-e-Shaloo station. The statistical results of the simulated flow data for the training and testing phase of ALM modeling with different number of fuzzy rules are presented in Table 1.

Table 1 shows that simulation of stream flow using precipitation, temperature, humidity and vapor pressure data present improper results. For example, in the best results (ALM model with 32 fuzzy rules) the values of Nash-Sutcliffe and R^2 don’t exceed from 0.40 in the testing phase. Nash-Sutcliffe efficiency coefficient value less than 0.5 are considered as unacceptable, while values greater than 0.6 are considered as good and greater than 0.8 are considered excellent results [29]. Therefore the statistical goodness of fit criteria demonstrate

Table 1: Statistical goodness of fit criteria for runoff simulation using ALM without discharge data as input variable at different number of fuzzy rules in the training and testing phase

	Nash-Sutcliffe		Bias		R2		MPAE		PTVE		RMSE		PW-RMSE	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
2 rules	0.31	0.13	6.2	133.4	0.31	0.31	82.5	114.1	1.40	45.2	315.6	293.7	403.0	431.0
4 rules	0.39	0.22	-2.2	109.9	0.41	0.35	72.3	108.4	-0.51	37.2	295.7	276.6	383.5	420.2
8 rules	0.43	0.24	-8.2	99.4	0.45	0.34	67.9	103.2	-1.80	33.7	286.9	273.0	374.5	420.5
16 rules	0.46	0.27	-23.8	83.8	0.49	0.34	62.0	95.5	-5.40	28.4	279.6	268.9	369.7	419.0
32 rules	0.47	0.29	-42.5	65.8	0.50	0.33	56.4	90.1	-9.70	22.3	276.3	265.4	367.7	418.9
64 rules	0.48	0.29	-53.7	51.8	0.51	0.31	52.5	86.5	-12.20	17.5	274.3	265.3	365.4	426.3
128 rules	0.49	0.28	-60.3	41.9	0.53	0.30	49.5	114.1	-13.70	14.2	270.1	266.6	358.9	435.7

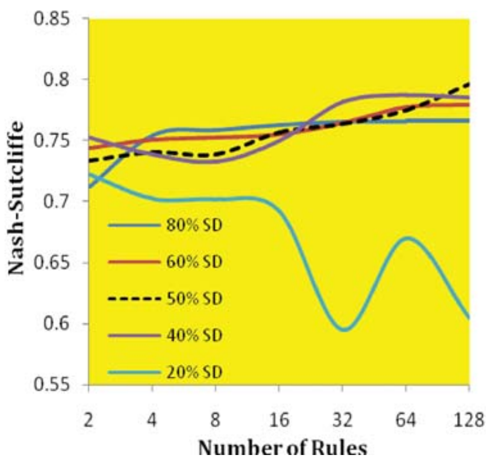

Fig. 4: Effect of changing fuzzy points on the NS values (model efficiency) of ALM model in the testing phase at different number of fuzzy rules (SD: Shared Data).

the inappropriate results of fuzzy modeling. Figures 5 and 6 show the comparison between simulated and observed hydrographs and scatter plot and Q-Q diagram of ALM model, developed using 32 fuzzy rules, respectively. These graphical criteria confirm that simulation has not performed in an appropriate manner.

The reason of this improper estimation of ALM is the very low correlation coefficient between inputs data (precipitation, temperture, humidity and vapor pressure) and output (discharge) (Table 2). Therefore, ALM could not estimate the stream flow from this data in an appropriate manner. In spite of conceptual model, ALM disregards the physics of problem and trying to extract the knowledge from the correlations between inputs data and output.

In addition, existence of very intense peaks, high kurtosis and skewness of input-output data, many outlier data, large area, very high elevation range and heterogeneous characteristics of watershed, long-term simulation and different conditions of modeling, scarcity of data gauges and lumped modeling of very large watershed are the factors of complexity of ALM modeling without discharge data as input variable.

Runoff Simulation with Discharge Data: According to Table 2, the appropriate correlation between discharge data can be observed. Hence, discharge data from 1 to 5 time lags were added to the previous input dataset. ALM was trained and tested with new dataset. Statistical results of ALM in training and testing phase have been presented in Table 3.

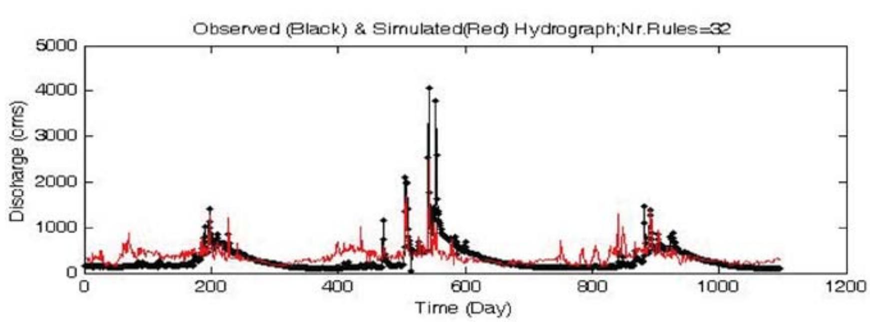

Fig. 5: Observed hydrograph (black line) and simulated hydrograph (red line) using ALM with 32 fuzzy rules in the test phase (discharge data were not used as input data)

Table 2: Correlation coefficient between input data with different time lags and output (discharge with lag 0)

Lags	Precipitation	Temperature	Humidity	Vapor pressure	Discharge
0	0.174	0.039	0.101	0.013	--
1	0.289	0.039	0.117	0.021	0.815
2	0.172	0.041	0.108	0.015	0.620
3	0.102	0.045	0.095	0.007	0.535
4	0.068	0.050	0.088	0.003	0.486
5	--	--	--	--	0.457

Table 3: Statistical goodness of fit criteria for ALM model at different fuzzy rules in training and testing phase

	Nash-Sutcliffe		Bias		R2		MPAE		PTVE		RMSE		PW-RMSE	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
2 rules	0.84	0.73	-7.9	19.7	0.84	0.75	19.6	34.5	-1.8	6.6	151	162	244	355
4 rules	0.85	0.73	-2.4	18.8	0.85	0.74	15.0	27.4	-0.56	6.4	147	162	240	357
8 rules	0.85	0.73	-1.8	11.7	0.85	0.74	12.0	19.6	-0.41	3.9	145	162	237	359
16 rules	0.85	0.74	-5.6	5.92	0.86	0.75	10.3	15.8	-1.20	2.0	143	158	235	357
32 rules	0.85	0.75	-10.0	1.30	0.86	0.75	9.20	13.0	-2.30	0.5	143	157	236	357
64 rules	0.85	0.75	-14.5	-1.2	0.86	0.76	9.31	12.5	-3.30	-0.4	146	157	239	357
128 rules	0.85	0.75	-14.9	-2.3	0.86	0.76	9.10	11.6	-3.40	-0.8	146	157	239	356

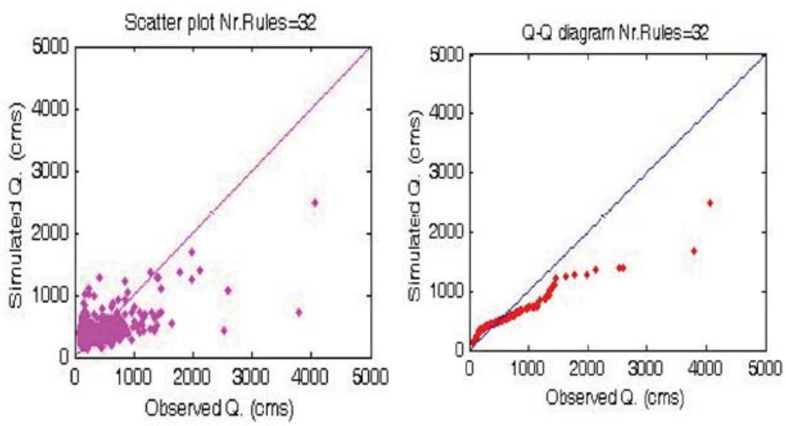

Fig. 6: Scatter plot and Q-Q diagram of ALM model with 32 fuzzy rules in the test phase (discharge data were not used as input data)

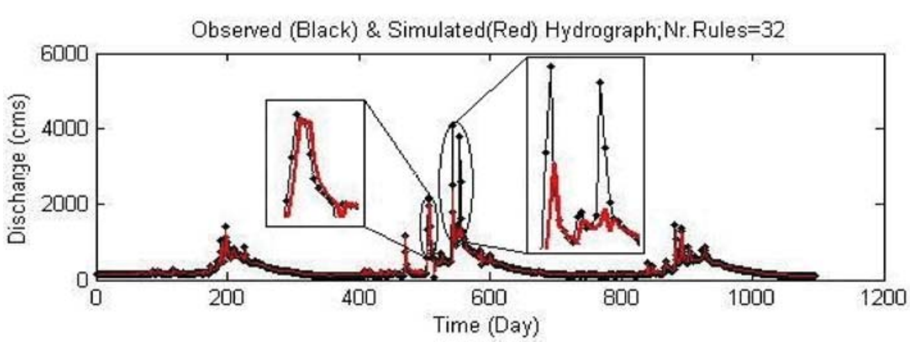

Fig. 7: Observed hydrograph (black line) and simulated hydrograph (red line) using ALM with 32 fuzzy rules in the test phase (discharge data were used as input data).

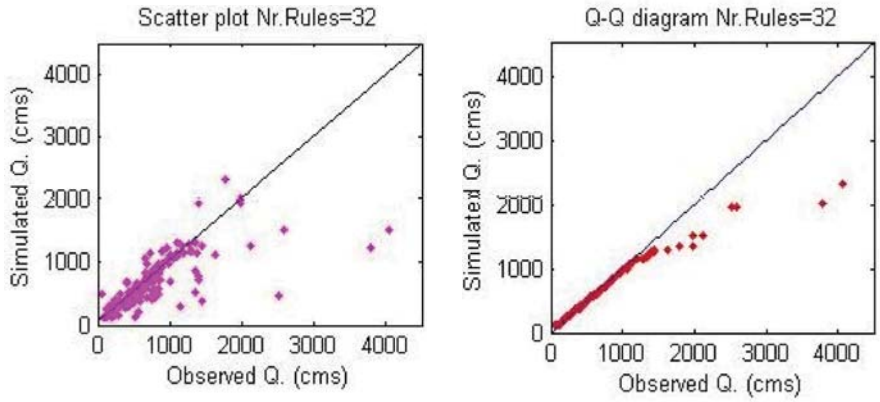

Fig. 8: Scatter plot and Q-Q diagram of testing phase with 32 fuzzy rules (discharge data were used as input data)

Table 4: Results of ranking the variables according to their roles in the dividing variable and one-variable functions

Variable	Number of used for Dividing variable	Number of used for 1-Variable function
Precipitation Lag0	0	0
Precipitation Lag1	4	0
Precipitation Lag2	1	0
Precipitation Lag3	1	0
Precipitation Lag4	0	0
Discharge Lag1	11	62
Discharge Lag2	3	0
Discharge Lag3	1	0
Discharge Lag4	0	0
Discharge Lag5	1	0
Temperature Lag0	0	0
Temperature Lag1	0	0
Temperature Lag2	0	0
Temperature Lag3	0	0
Temperature Lag4	0	0
Humidity Lag0	8	0
Humidity Lag1	0	0
Humidity Lag2	0	0
Humidity Lag3	1	0
Humidity Lag4	0	0
Vapor Pressure Lag0	0	0
Vapor Pressure Lag1	0	0
Vapor Pressure Lag2	0	0
Vapor Pressure Lag3	0	0
Vapor Pressure Lag4	0	0

Table 3: shows that the ALM could simulate the stream flow appropriately. In addition, after 32 rules (64 and 128 rules) there is no significant improvement in the ALM simulation results. Hence, ALM model with 32 rules is chosen as the best ALM model. Comparison of Table 1 and 3 shows the role of basin discharge in the modeling results. ALM could truly identify the appropriate variables and extract the knowledge of the dataset. Figure 7 shows the comparison between observed hydrographs and simulated hydrograph using ALM with 32 fuzzy rules. In Figure 8, scatter plot and Q-Q diagram of ALM modeling with 32 fuzzy rules are presented. According to these graphical results, it is possible to judge that ALM has been able to simulate runoff appropriately. But the hydrograph (Figure 7) and scatter plot and Q-Q diagram (Figure 8) imply that for the high values of discharge and peak values, the ALM underestimate the runoff values. This subject can be proved by higher PW-RMSE values than RMSE.

Totally, ALM with 32 fuzzy rules could simulate the stream flow and present appropriate results.

It is very easy to find the important or divided variables and one-variable function in each step of the ALM modeling. Consequently, the variables can easily be ranked according to their roles in modeling. Consider the ranking criterion for variables; used in one-variable functions is the number of subspaces that have been estimated using each variable. The results of ranking using this method has been presented in Table 4 and it shows that the most important variable is discharge with one time lag (62 times). According to Table 2, ALM could find the best variable for modeling.

Similarly, suppose that the ranking criterion for the variables; used for dividing is the dividing times for each variable. Hence, according to Table 4, discharge with one time lag (eleven times) is the most important variable for dividing the space. Then humidity with lag 1, precipitation with lag 1 and discharge with lag 2 were determined as other important variables for dividing of space of variables in runoff simulation problem. In addition, Table 4 shows that vapor pressure and temperature have no role in the modeling and these variables are unnecessary variables for modeling.

According to these results, the ALM is able to find and rank the effective variables in complicated nonlinear systems. Therefore, the ALM modeling can be performed using the mentioned data instead of many different variables and different time lags, utilized in this study.

CONCLUSION

The ALM is not sensitive to the fuzzy dividing points and NS values for different fuzzy dividing points are almost equal.

When the daily temperature, vapor pressure, precipitation and humidity data with different time lags were utilized as inputs for daily runoff modeling by ALM, the modeling results are not so good. The best ALM model had 32 fuzzy rules. NS, R^2, Bias, RMSE, PWRMSE and PTVE of the tested ALM model with 32 fuzzy rules for daily runoff modeling were 0.29, 0.33, 65.8 (cms), 265.4 (cms), 418.9 (cms) and 22.3%. This weakness is highly related to the very low correlation coefficient between input variables and output (river discharge).

When the discharge data with different lags are added to the list of input variables, the results of daily runoff modeling by ALM improved very much and the ALM presented appropriate daily runoff simulation. Again, the best ALM model had 32 fuzzy rules. NS, R^2, Bias, RMSE, PWRMSE and PTVE of the tested ALM model with 32 fuzzy rules for daily runoff modeling were 0.75, 0.75, 1.3 (cms), 157 (cms), 357 (cms) and 0.5%.

ALM has some advantages that there is no in other famous artificial intelligence methods such as ANN and ANFIS. ALM training is not time consuming and it is very easy and straightforward. In addition, ALM could find and rank the input variables and remove the unnecessary variables from modeling. In the daily runoff simulation, ALM found that discharge with one day lag is the best variable for modeling and it found that the other important variables are precipitation and humidity. In addition, ALM found that temperature and vapor pressure are unnecessary variables and removed them from modeling. In general, the modified ALM, used as the first time for daily runoff modeling, has merit to be introduced as a novel and appropriate modeling method for the runoff simulation.

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