Application of Soft Compiting Techniques in River Flow Modeling in The Case of Euphrates-Tigres Basin

Tables

TABLE 1 Selected stream stations in the Euphrates-Tigris Basin.

Station number	Name	Longitute-latitute	Mean (flow) (m^3/sn)	Max (flow) (m^3/s)	Min (flow) (m^3/s)	Standart deviation (flow)
2102	Murat Rıver - Palu	(39° 56' 22" E - 38° 41' 49" N)	179,23	997	12,1	207,606
2122	Murat Rıver- Tutak	(42° 46' 49" E - 39° 32' 19" N)	47,48	821	1,97	73,041
2124	Tohma Bourn - Yazıkoy	(37° 26' 33" E - 38° 40' 21" N)	6,605	59,8	0,425	3,855
2131	Bey Stream - Kılayık	(38° 12' 36" E - 38° 19' 21" N)	1,343	38,8	0,11	1,894
2135	Bulam Stream - Fatopasa	(38° 14' 13" E - 37° 59' 38" N)	3,624	27,3	0,844	2,438
2145	Tohma Bourn - Hısarcık	(37° 41' 08" E - 38° 28' 32" N)	20,019	251	5,53	13,285
2149	Munzur Bourn - Mıskısag	(39° 32' 35" E - 39° 06' 29" N)	24,714	274	5,53	23,045
2151	Fırat Rıver - Demirkapı (Sansa)	(40° 10' 05" E - 39° 34' 41" N)	58,863	712	4,07	74,378

2156	Karasu - Asagıkagdarıc	(38° 26' 55" E - 39° 25' 57" N)	150,9272	980	54,8	116,844
2158	Bingöl Stream - Abdurrahman paşa Brıdge	(41° 29' 14" E - 39° 06' 30" N)	18,4965	338	1,3	29,181
2164	Goynuk Stream - Çayagzı	(40° 33' 17" E - 38° 48' 06" N)	32,497	630	0,45	56,143
2166	Perı Bourn - Logmar	(39° 48' 50" E - 38° 51' 31" N)	76,742	967	0,55	96,458
2610	Bıtlıs Stream - Baykan	(41° 46' 57" E - 38° 09' 41" N)	17,969	420	1,95	24,602
2612	Batman stream - Malabadı Brıdge	(41° 12' 16" E - 38° 09' 16" N)	112,848	990	0,015	150,300

TABLE 2 Model Results of Murat River- Palu (2102) station.

			TRAIN								TEST									
		TRIAL NO	RMSE	RANK	MSE	RANK	R	RANK	MAE	RANK	RMSE	RANK	MSE	RANK	R	RANK	MAE	RANK	TOTAL RANK	
Evaluation According To The Method	ELM	Q(t-1)-Q(t)	62,03	4	3.847,50	4	0,9873	4	0,12	5	53,09	3	2.819,06	3	0,9815	4	0,70	4	31	
		Q(t-2)+Q(t-1)-Q(t)	56,36	4	3.176,19	4	0,9898	4	0,23	5	46,02	4	2.118,20	4	0,9847	4	1,56	3	32	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	67,35	2	4.535,52	2	0,9884	2	0,28	5	49,82	4	2.481,69	4	0,9820	3	2,17	4	26	89
	ANFIS	Q(t-1)-Q(t)	63,02	3	3.970,92	3	0,9873	3	0,94	3	53,07	4	2.816,83	4	0,9814	3	0,27	5	28	
		Q(t-2)+Q(t-1)-Q(t)	76,59	1	5.866,19	1	0,9822	1	3,27	3	60,50	1	3.660,17	1	0,9741	1	5,29	2	11	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	100,60	1	10.120,12	1	0,9746	1	3,31	3	75,10	1	5.639,93	1	0,9629	1	6,89	3	12	51
	SVM	Q(t-1)-Q(t)	66,04	1	4.361,10	1	0,9798	1	22,75	2	50,58	5	2.558,79	5	0,9814	2	2,16	2	19	
		Q(t-2)+Q(t-1)-Q(t)	61,65	2	3.800,50	2	0,9849	3	19,60	2	45,68	5	2.086,61	5	0,9846	3	1,00	5	27	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	62,90	3	3.956,00	3	0,9849	3	28,96	1	47,15	5	2.223,45	5	0,9845	4	8,44	2	26	72
	GPR	Q(t-1)-Q(t)	50,10	5	2.509,90	5	0,9899	5	0,45	4	54,33	1	2.951,49	1	0,9804	1	0,85	3	25	
		Q(t-2)+Q(t-1)-Q(t)	6,93	5	1,48	5	0,9897	5	1,94	4	55,42	2	3.071,47	2	0,9831	2	1,45	4	29	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	1,27	5	1,60	5	0,9953	5	0,48	4	57,63	2	3.320,83	2	0,9790	2	1,22	5	30	84
	ENN	Q(t-1)-Q(t)	65,82	2	4.332,70	2	0,9824	2	23,27	1	54,12	2	2.928,30	2	0,9840	5	21,98	1	17	
		Q(t-2)+Q(t-1)-Q(t)	61,14	3	3.738,20	3	0,9849	2	20,75	1	50,04	3	2.503,70	3	0,9864	5	20,31	1	21	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	61,02	4	3.723,00	4	0,9849	4	20,69	2	49,82	3	2.481,80	3	0,9865	5	20,10	1	26	64
	TOTAL									1680								1680		
Evaluation by Data Combination	ELM	Q(t-1)-Q(t)	62,03	2	3.847,50	2	0,9873	1	0,12	3	53,09	1	2.819,06	1	0,9815	1	0,70	3	14	
		Q(t-2)+Q(t-1)-Q(t)	56,36	3	3.176,19	3	0,9898	3	0,23	2	46,02	3	2.118,20	3	0,9847	3	1,56	2	22	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	67,35	1	4.535,52	1	0,9884	2	0,28	1	49,82	2	2.481,69	2	0,9820	2	2,17	1	12	
	ANFIS	Q(t-1)-Q(t)	63,02	3	3.970,92	3	0,9873	3	0,94	3	53,07	3	2.816,83	3	0,9814	3	0,27	3	24	
		Q(t-2)+Q(t-1)-Q(t)	76,59	2	5.866,19	2	0,9822	2	3,27	2	60,50	2	3.660,17	2	0,9741	2	5,29	2	16	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	100,60	1	10.120,12	1	0,9746	1	3,31	1	75,10	1	5.639,93	1	0,9629	1	6,89	1	8	
	SVM	Q(t-1)-Q(t)	66,04	1	4.361,10	1	0,9798	1	22,75	2	50,58	1	2.558,79	1	0,9814	1	2,16	2	10	
		Q(t-2)+Q(t-1)-Q(t)	61,65	3	3.800,50	3	0,9849	3	19,60	3	45,68	3	2.086,61	3	0,9846	2	1,00	3	24	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	62,90	2	3.956,00	2	0,9849	2	28,96	1	47,15	2	2.223,45	2	0,9845	2	8,44	1	14	
	GPR	Q(t-1)-Q(t)	50,10	1	2.509,90	1	0,9899	1	0,45	3	54,33	3	2.951,49	3	0,9804	3	0,85	3	17	
		Q(t-2)+Q(t-1)-Q(t)	6,93	2	1,48	3	0,9897	3	1,94	1	55,42	2	3.071,47	2	0,9831	3	1,45	1	17	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	1,27	3	1,60	2	0,9953	2	0,48	2	57,63	1	3.320,83	1	0,9790	1	1,22	2	14	
	ENN	Q(t-1)-Q(t)	65,82	1	4.332,70	1	0,9824	1	23,27	1	54,12	1	2.928,30	1	0,9840	1	21,98	1	8	
		Q(t-2)+Q(t-1)-Q(t)	61,14	2	3.738,20	2	0,9849	2	20,75	2	50,04	2	2.503,70	2	0,9864	2	20,31	2	16	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	61,02	3	3.723,00	3	0,9849	3	20,69	3	49,82	3	2.481,80	3	0,9865	3	20,10	3	24	
COMBINATION TOTAL		Q(t-1)-Q(t)	73,00		Q(t-2)+Q(t-1)-Q(t)				95,00		Q(t-3),Q(t-2), Q(t-1)-Q(t)						72			

Perfect coefficient of variation (R) = 1, perfect root-mean-squared error (RMSE) = 0, perfect mean absolute error (MAE) = 0, perfect MSE = 0

TOTAL RANK (Evaluation According To The Method)

STATION	Q(t-1)-Q(t)					Q(t-2)+Q(t-1)-Q(t)					Q(t-3),Q(t-2), Q(t-1)-Q(t)				
	ELM	ANFIS	SVM	GPR	ENN	ELM	ANFIS	SVM	GPR	ENN	ELM	ANFIS	SVM	GPR	ENN
2151	24	31	18	25	22	34	12	22	27	25	35	13	19	30	23
TOTAL	376	387	268	366	283	450	249	292	368	321	427	196	315	385	357
COMBINATION TOTAL			1680					1680					1680		
TOTAL ELM	1253	TOTAL ANFIS	832	TOTAL SVM	875	TOTAL GPR	1119	TOTAL ENN	961						

TOTAL RANK (Evaluation by Data Combination)

STATION	Q(t-1)-Q(t)	Q(t-2)+Q(t-1)-Q(t)	Q(t-3),Q(t-2), Q(t-1)-Q(t)	TOTAL
2102	73	95	72	240
2122	66	83	91	240
2124	64	86	90	240
2131	75	87	78	240
2135	72	79	89	240
2145	68	87	85	240
2149	63	89	88	240
2151	61	75	104	240
2156	66	81	93	240
2158	67	82	91	240
2164	72	72	96	240
2166	83	73	84	240
2610	67	75	98	240
2612	69	81	90	240
COMBINATION TOTAL	966	1145	1249	3360

APPENDIX A Applicability of ANFIS, ELM, ENN, SVM and GPR approaches and streamflow forecasting, and hydrologic engineering fields.

Hydrological Processes	Scholars & Case study location	Time scale	Predictive models	Unique aspects or salient features
Precipitation Forecast	(Akrami et al. 2014)/ Malaysia	Monthly	connecting the wavelet decomposition method to ANFIS, ANFIS, ANN	It was recommended to make precipitation prediction by connecting the wavelet decomposition method to ANFIS and artificial neural networks. As a result of the study, it was seen that ANFIS based on wavelet decomposition performed better than ANN and ANFIS.
	(Mokhtarzad et al. 2017) /Tehran	Monthly	YSA, SVM, ANFIS (ın addıition to SPI)	In this study in which YSA, SVM and ANFIS techniques were compared for precipitation prediction, the input parameter was used as temperature, humidity and precipitation while the output parameter was SPI. In addition to the

				high accuracy of all models, SVM was found to provide the best performance.
	(Choubin et al. 2018)/ Iran	Time Series	Classification and regression trees (CART), ARIMA, ANFIS	CART, ARIMA and ANFIS were used for precipitation estimation and these methods were compared. It was seen that the CART method gave better results.
	(Li et al. 2018) / China	Monthly	variational mode decomposition (VMD), ELM, back propagation (BP) and Elman	In the study, ELM and VMD were used to make estimations through precipitation time series. Then, a comparison was made with the hybrid models BP and Elman neural network. It was observed that ELM gave better results than the others.
Evapotranspiration	(Ferreira et al. 2019) / Brazil	Daily	SVM, K-means, Cluster	SVM was used for evapotranspiration estimation. In addition, k-means and clustering method were used to group the meteorology stations. In this way, the performance of the models increased.
	(Tao et al. 2018)/Burkina Faso	Daily	ANFIS, ANFIS-FA	ANFIS-FA, a new hybrid intelligent ANFIS model, was proposed for evapotranspiration prediction. The model was created with a large number of meteorological inputs and it provided good performance .
	(Han et al. 2019)/ China	Monhly	XGBoots, multivariate adaptive regression splines (MARS), GPR	In this study in which evapotranspiration was estimated by comparing XGBoost, MARS and GPR techniques, it was concluded that the MARS model was superior.
Drought	(Khan et al. 2020)/ Pakistan	Time series	SVM, k-Nearest Neighbour (KNN) and Standardized Precipitation Evaporation Index (SPEI)	In this study, the first drought prediction for Pakistan, SVM and KNN were used, and SPEI was used for drought calculations.
	(Zhang et al. 2020)/ China	Yearly	autoregressive integrated moving	Drought analysis was carried using SPEI drought index, and drought

			average (ARIMA), wavelet neural network (WNN), SVM	prediction modelling was performed with ARIMA, WNN and SVM. It was seen that ARIMA model gave better results.
	(Mokhtarzad et al. 2017)/Khorasan	3 monthly	artificial neural network (ANN), SVM, ANFIS, SPI	Drought analysis was performed by comparing ANN, SVM and ANFIS models, it was observed that the SVM model gave better results.
Air Quality	(Ghasemi and Amanollahi 2019)/ Kermanshah	Daily	ANFIS, forward selection (FS)	In this study, in which air quality was examined through ANFIS, FS and ANFIS models were developed and it was found to be a suitable method for air quality examinations.
	(Bhardwaj and Pruthi 2020)/ India	Time series	particle swarm optimization (PSO) and genetic algorithm (GA)	In order to analyse an air pollutant, PSO and GA were used together with the ANFIS model, and as a result of this integration, it was seen that the model providing the best performance was ANFIS-PSO.
Soil Moisture	(Li et al. 2019)/ China	Time series	GPR	The results of the study, in which GPR was used for soil moisture and temperature estimation, show that GPR is better in predicting soil moisture.
	(Ji et al. 2019)/Hulan	Time series	stochastic weight particle swarm optimization algorithm (RandWPSO), ELM	In this study, ELM and RandWPSO models were used to measure soil moisture quality and to test the usability of ELM. The accuracy level of ELM was found quite high.
Water Level Estimation	(Hipni et al. 2013)/ Malaysia	Daily	SVM, V-fold cross-validation and the time lag	SVM was used to estimate the daily dam water level, SVM was used together with V-fold cross-validation and the time lag to find the best result. The best result (R; amount of precipitation, L; water level) was achieved in combination of R(t-2) L(t-2).
	(Deo and Şahin	Monthly	ANN, ELM	In the study in which water level

	2016)/ Eastern Queensland			estimation was performed using ANN and ELM models, it was concluded that ELM was superior in water level prediction.
	(Khan and Coulibaly 2006)/ North America	3-12 monthly	SVM, multilayer perceptron (MLP), seasonal autoregressive model (SAR)	In the study in which long-term estimation of lake water levels was made using SVM, SVM was compared with common artificial neural networks MLP and SAR, and it was seen that SVM gave better results.
Water Quality	(Azad et al. 2019)/ The Zayandehrood Basin	Time series	evolutionary algorithm(EA), ANN , ANFIS, ANFIS-PSO	In the study investigating the water quality using ANFIS, ANN and EA, those models were compared with ANFIS-PSO and it was seen that ANFIS-PSO gave better results.
Evaporation	(Mohamadi et al. 2020)/Mianeh and Yazd	Monthly	Shark algorithm (SA), d frefy algorithms (FFA),multilayer perceptron (MLP) radial basis function (RBF), ANFIS	ANFIS, RBF, MLP, RBF-SA, MLP-SA, RBF-FFA, MLP-FFA models were used for monthly evaporation estimation. It was observed that the ANFIS model gave better results when developed.
Sediment Transportation	(Safari et al. 2019)	Time series	Gene Expression Programming (GEP), ELM, Generalized Structure Group Method of Data Handling (GS-GMDH) ,Fuzzy c-means(FCM), FCM-ANFIS	In the study investigating sediment transport in open channels through GEP, ELM, GS-GMDH, FCM-ANFIS models, it was observed that GS-GMDH model gave better results.
Discharge Coefficient	(Azimi et al. 2017)	Time series	ELM	Genetic Algorithm (GA) - Least Square Estimator (GL) and adaptively developed ANFIS were used as R(ANFIS) and R-ANFIS(GL) for river stream modelling. It was seen that the R-ANFIS (GL) model

				gave better results.
River Stream Estimation	(Zhou et al. 2019)/ China	Time series	R-ANFIS, R-ANFIS(GL)	Genetic Algorithm (GA) - Least Square Estimator (GL) ve uyarlanabilir şekilde geliştirilmiş ANFIS; R(ANFIS) ve R-ANFIS(GL) şeklinde nehir akımı modellemesi için kullanılmıştır. Çalışmada R-ANFIS(GL) modelinin daha iyi sonuç verdiği görülmüştür.
	(He et al. 2014)/ China	Monthly	ANN, ANFIS, SVM	ANN, ANFIS and SVM were used in the study in which three different data-based models were used for river stream estimation. It was observed that SVM provided better performance than other methods and it was stated that these methods could be used in regions with complex topography.
	(Rezaeianzadeh et al. 2014)/ Iran	Daily	multiple linear regression (MLR) ,multiple nonlinear regression (MNLR), ANN, ANFIS	NN, ANFIS, MLR and MNLR were used to estimate the maximum daily stream. In this study in which precipitation and stream data were used in different combinations for simulations, it was stated that the MNLR model was superior.
	(Yaseen et al. 2019)/ Malaysia	Daily	EELM, ELM, SVM	In the study in which the ELM model was developed and compared with SVM in the form of EELM, it was seen that the developed ELM model has much superior features.
	(Yaseen et al. 2016)/ Malaysia	Daily	ELM, SVR, single-layer feedforward neural network (SLFN)	In the study in which ELM, SVR (SVM) and SLFN models were used, ELM was suggested for river stream modelling and it was found that ELM was superior to other models.
	(Adnan et al. 2019)	Daily	ELM-ANFISPSO, multivariate adaptive regression	In the study in which ELM was developed and used as OP-ELM, ANFIS PSO, MARS and M5Tree models were compared with OP-ELM and it was stated that OP-ELM

		splines(MARS), M5 model tree (M5Tree)	was superior to other methods.
(Yaseen et al. 2020)/ Australia	Hourly	ENN, MARS, RVM, MPMR	In the study in which ENN, Multivariate adaptive regression splines (MARS), Minimax Probability Machine Regression (MPMR), Relevance Vector Machine (RVM) methods were applied for hourly river stream modelling, ENN was proposed for the first time for river stream and it was found to be superior to other models.
(Sun et al. 2014)/ ABD	Daily	GPR	In the study in which river stream estimations were made by using GPR for MOPEX basins, it was concluded that GPR performed well when long-term stream data were used.