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Application of Stochastic Models to Annual Extreme Streamflow Data

Karim Hamidi Machekposhti, Hossein Sedghi

***Abstract*—**This study was designed to find the best stochastic model (using of time series analysis) for annual extreme streamflow (peak and maximum streamflow) of Karkheh River at Iran. The Auto-regressive Integrated Moving Average (ARIMA) model used to simulate these series and forecast those in future. For the analysis, annual extreme streamflow data of Jelogir Majin station (above of Karkheh dam reservoir) for the years 1958–2005 were used. A visual inspection of the time plot gives a little increasing trend; therefore, series is not stationary. The stationarity observed in Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) plots of annual extreme streamflow was removed using first order differencing (d=1) in order to the development of the ARIMA model. Interestingly, the ARIMA(4,1,1) model developed was found to be most suitable for simulating annual extreme streamflow for Karkheh River. The model was found to be appropriate to forecast ten years of annual extreme streamflow and assist decision makers to establish priorities for water demand. The Statistical Analysis System (SAS) and Statistical Package for the Social Sciences (SPSS) codes were used to determinate of the best model for this series.

***Keywords*—**Stochastic models, ARIMA, extreme streamflow, Karkheh River.

I. Introduction

ACCURATE simulation and forecasting of water availability is a key step in efficient planning, operation, and management of water resources. Developing reliable surface water flow forecasting methods for real time operational water resources management becomes increasingly important. Various approaches, including physical and mathematical models, have been used for this purpose. The problems water resources in a region can check by stochastic hydrologic methods, thus this method is very important for hydrologists. The most important model of this method are time series models (ARMA or ARIMA models) that these models were developed extensively since the 1960s and were used by many researchers in the world. Time series analysis [1] has been widely used in the field of hydrology and water resources for simulation and forecasting [3].

Time series analysis is effective instrumentations for selecting a model that demonstrates the past behavior of historical data. With this analysis and select the best model, we are able to predict future events such as rainfall. Many studies in this subject have specified that stochastic time series models are very useful and effective to predict. References [1], [15], [17] have developed around ARIMA models and their extensions. Shakeel et al. applied time series to modelling of annual maximum flow in River Indus at Sukkur India. They found that ARIMA (2,1,1) model was appropriate for this series [11]. Srikanthan et al. used time series models to analyse annual flow of Australian streams. ACF and PACF were applied to determine the appropriate form of Box-Jenkins time series models [12].

Stojković et al. studied stochastic structure of annual discharges of large European rivers. They suggested that the stochastic flows simulated by the model can be used for hydrological simulations in river basins [13]. Huang et al. analyzed annual maximum stage readings of three rivers in Langat River basin in Malaysia for forecasting of flood using stochastic model (ARIMA). They found that ARIMA(1,1,0), ARIMA(1,1,0) and ARIMA(1,1,1) are the best models for the Dengkil, Kg. Lui and Kg. Rinching series respectively [4]. Tian et al. studied extreme value analysis of stream flow time series in Poyang Lake Basin, China [14]. During the last decades, several studies have developed methods of analyzing stochastic characteristics of streamflow time series [2], [5]-[10], [16], [18].

In this study, linear stochastic models known as nonseasonal ARIMA models were used to model annual extreme streamflow for Karkheh River at Iran. The study area is located on latitudes 31^0 48′ and 34^0 58′ N and longitudes 46^0 57′ and 49^0 10′ E with its elevation ranging 1216 meter. The Kakheh River is formed of two main branches of Saymareh and Kashkan rivers and is one of the rivers the in southwestern of Iran, which flows in the southern of Khuzestan provinces. With 900 kilometres in length, it is known as the third long river in Iran. In this study, extreme streamflow data for the Karkheh River at Jelogir Majin gauging station (upstream of Karkheh dam) were obtained from the Iran Water Resources Management Organization (IWRMO), covering the period 1958–2015. It includes a length of 58 years observations. Fig. 1 showed Karkheh River basin.

II. Methods

A stationary time series data which have constant mean and variance, can be modelled in different ways and process: Auto Regressive (AR), Moving Average (MA), or Auto Regressive and Moving Average (ARMA). When the data are stationary, we can use ARMA model but if data are not stationary, we need to use differencing on data series. These models are called ARIMA models.

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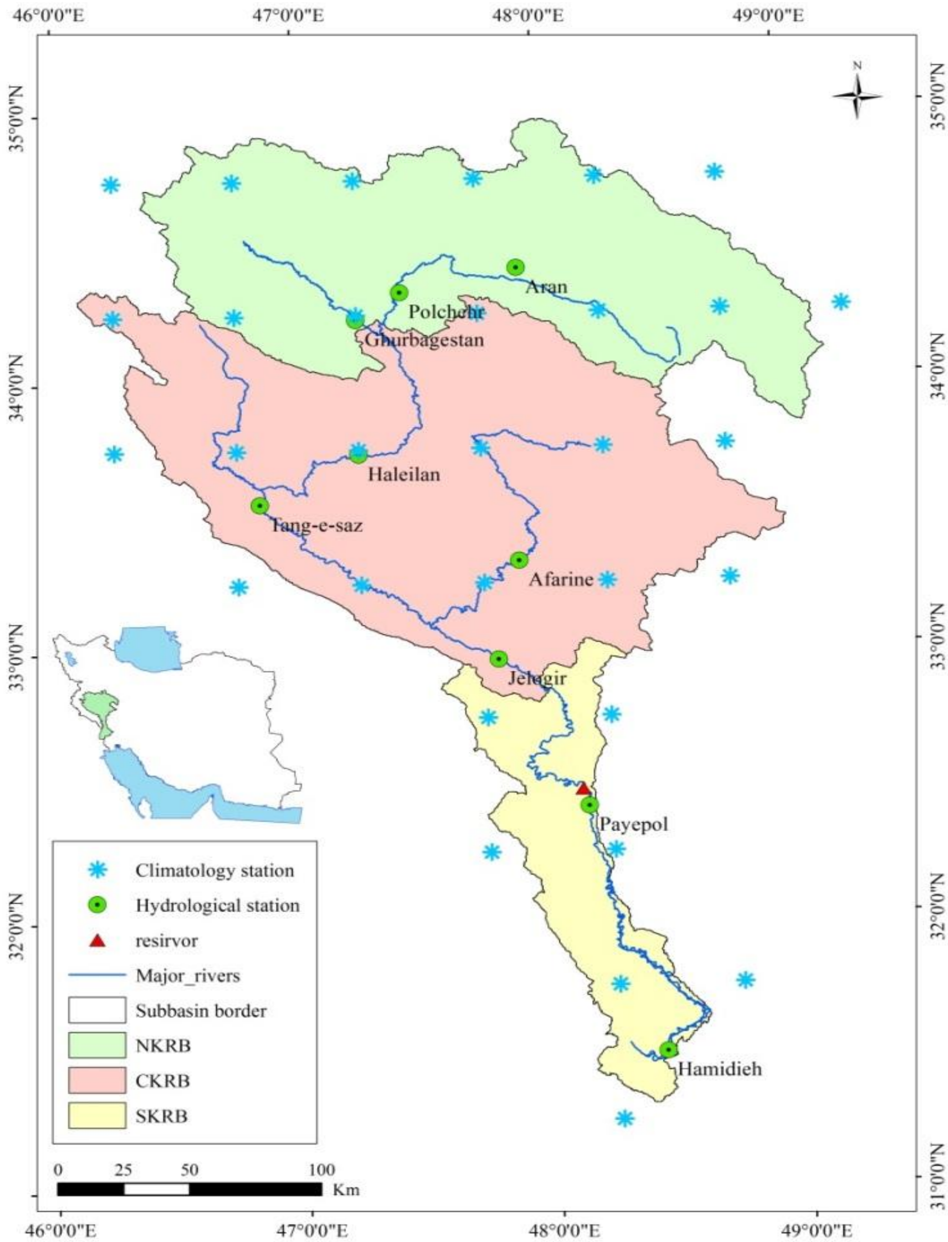

Fig. 1 The Karkheh River Basin

The general model of the non-seasonal ARIMA family is classified by three parameters p,d,q where p and q are degree (order) of AR and MA in model. The letter "d" is on dth difference of the time series. The amounts of p,d,q can be zero or positive in a general non-seasonal ARIMA model.

$$(B)\nabla^d X_t = (B)_t \tag{1}$$

where (B) and $\theta(B)$= Polynomials of order p and q, respectively.

$$\phi\ (B)= 1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_P B^p \tag{2}$$

and

$$(B)= 1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q \tag{3}$$

Four basic stages of ARIMA in identifying patterns in time series data and forecasting are model identification, parameter estimation, diagnostic checking and forecasting.

A. Model Identification Stage

In this stage, the number of auto-regressive (p) and moving average (q) parameters necessary to yield an effective model of the process is decided. The data are examined to check for the most appropriate class of ARIMA processes through selecting the order of the regular and nonseasonal differencing required to make the series stationary, as well as through specifying the number of regular and auto-regressive and moving average parameters necessary to adequately represent the time series model. The plots of the series with correlograms of ACF and PACF are the major tools for the identification phase. Correlograms are plot of auto correlation and partial auto correlation verses lag. In a time series, amount of linear dependence between data can be expressed by plotting of ACF and determinate of auto regressive term for manifest of trend, either in the average level or in the variance level of the series, by plotting of PACF.

B. Parameter Estimation Stage

At the parameter estimation stage, the parameters are estimated using by the Maximum Likelihood (ML), Conditional Least Square (CLS) and ULS methods. Among these methods, ML seems to be the best [1]. The parameters should be statistically significant at α=p% and should satisfy two conditions, namely stationary and invertibility for auto-regressive and moving average models, respectively. In this stage, several models are tentatively chosen and then compute the values of Akaike Information Criterion (AIC). The model structure which has the minimum AIC value, among others model structures, will be chosen as the best model. Equation (4) describes the formula to compute AIC. In this equation, Tp is the number of AR, I and MA parameters.

$$AIC = -2\,Ln\,(Max.Likelihood) + \frac{2T_p}{n - T_p - 1} \qquad (4)$$

C. Diagnostic Check Stage

After different models have been fitted to the data, it is important to perform diagnostic checks to test the adequacy of each model. First test is to check the residuals by using ACF and PACF graph. If the selected model is appropriate, the residuals graphs of both correlation functions should be white noise, indicating no remaining correlation.

The second test is Port Manteau lack of fit test (5). If the values of p-value in this test exceed 5%, it indicates that residuals have significant departure from white noise. If the selected model fails to pass Port Manteau lack of fit test, the modeler returns to select alternative model and follows the same procedure until satisfactory model results are obtained.

$$Q = (N - d - DS)\sum_{k=1}^{M} r_k^2 a_t \qquad (5)$$

In (5), r_k (a_t) is the auto-correlation coefficient of the residual (a_t) at lag k, and M is the maximum lag considered (about N/4), ARIMA model is considered adequate if p>chi square is greater than 0.05 where 0.05 is the level of significant.

D. Forecasting Stage

At the forecasting stage, the estimated parameters are used to calculate new values of the time series and assurance periods for forecasted values. The estimation process is applied on transformed (differenced) data, hence before prediction and production of data series the series needs to be integrated to thwart the effect of differencing so that the predicts are expressed in values suitable with the input data. The letter "I" in ARIMA model represents this automatic integration feature. To evaluate the performance of the best ARIMA model at each station, coefficient of determination (R^2) is used to select the best model. R^2 gives impartial result as it takes mean values of both the observed and predicted data.

In the present study, to identify the best fitted model, the predicted values using the several different ARIMA models are compared to the observed data of the validation period (2006-2015). The SAS and SPSS codes were used for all the analytical work. The basic methodology of ARIMA modelling is shown in Fig. 2:

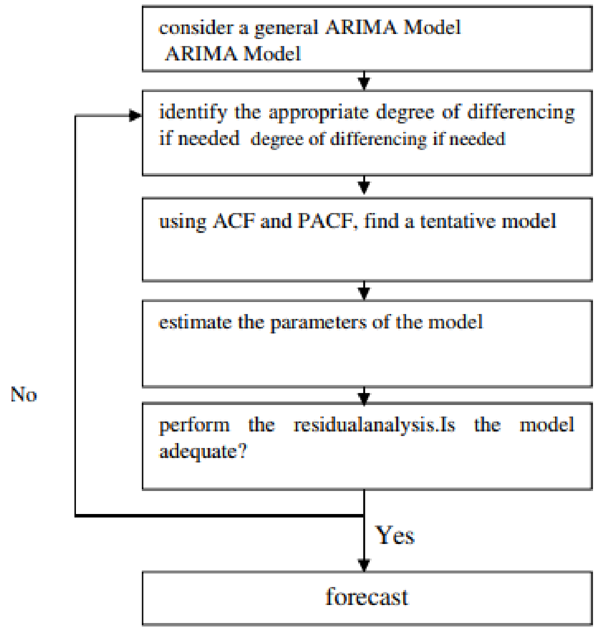

Fig. 2 ARIMA model development

III. RESULT AND DISCUSSION

A. Fitting Box-Jenkins

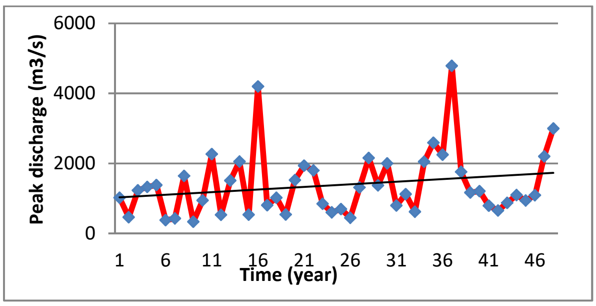

Fig. 3 Time series of annual peak streamflow of Karkheh River (1958–2005) in (m^3/s)

The time series model development consists of three stages: identification, estimation and diagnostic, see [9]. In the identification stage, data transformation is often needed to make the time series stationary. During the estimation stage, the model parameters are calculated by different method.

Finally, diagnostic check test of the model is performed to reveal possible model inadequacies to assist in the best model selection.

B. Identification of Representative Models

Model computation was made with extreme streamflow annual data from between 1958 to 2015. The dataset from 2006 to 2015 was considered in forecasting estimations of the model. The time series plot was conducted using the annual extreme streamflow data for Karkheh River at Jelogir Majin gauge station to assess the stability of the data, and Figs. 3 and 4 were obtained. The plots show that there is a little increasing of the series, and the series are nonstationary. Also, from the plot of the ACF and PACF of the annual data, Figs. 5 and 6, it has been found that the data must be differenced by one nonseasonal degree of differencing to achieve stationary (d=0). Differencing for nonseasonal ARIMA was not done due to absence of trends in the datasets. Figs. 7 and 8 confirm that the ACF and PACF plots for the differenced data (d=1) were stable, and the ARIMA model (p,1,q) could be identified for further analysis.

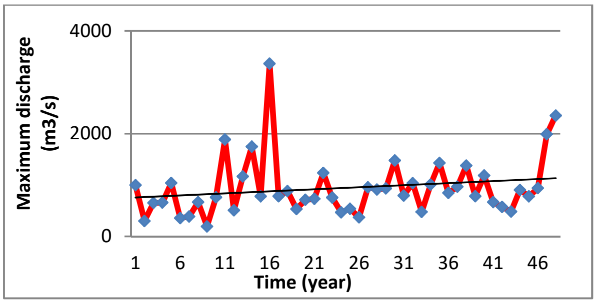

Fig. 4 Time series of annual maximum streamflow of Karkheh River (1958–2005) in (m^3/s)

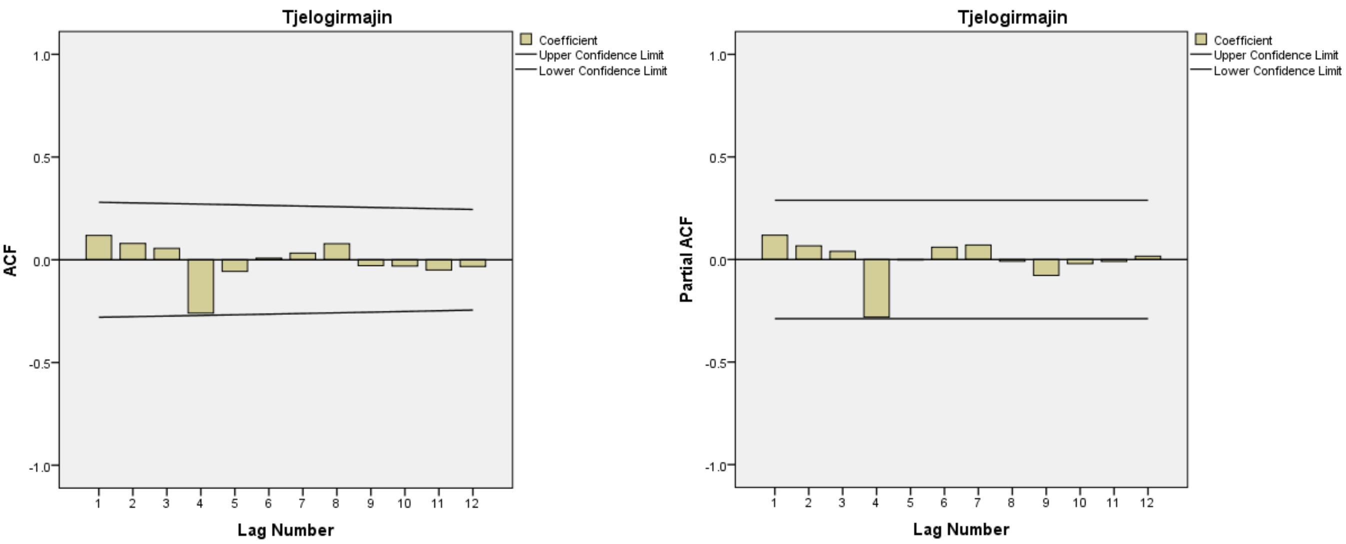

Fig. 5 ACF and PACF Plots of natural annual peak streamflow of Karkheh River (d=0)

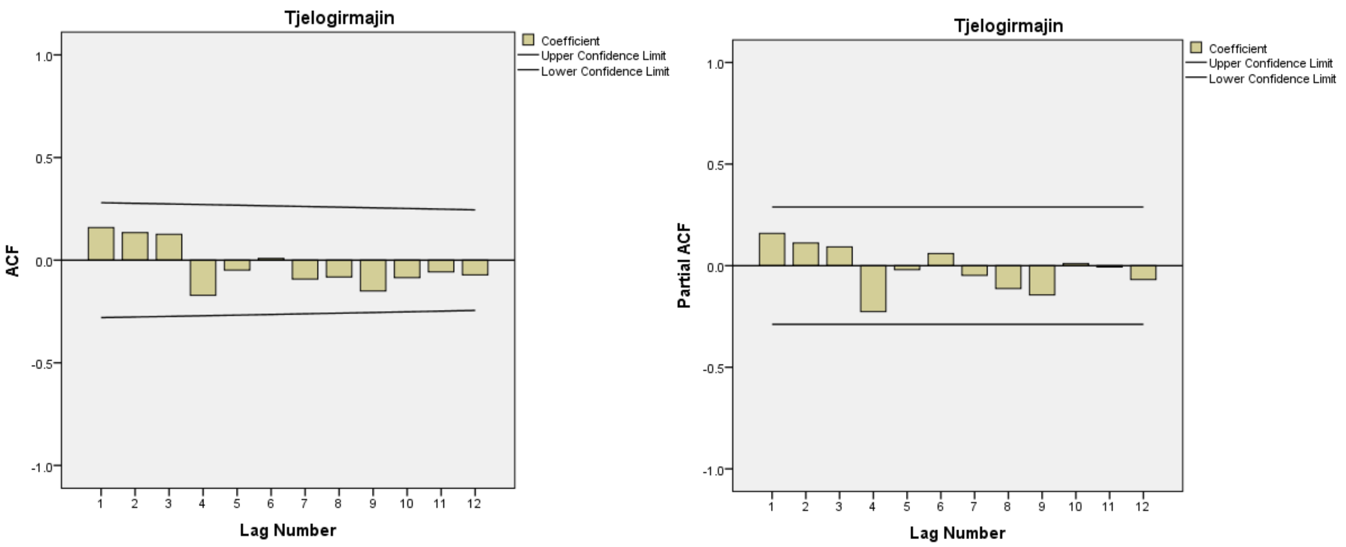

Fig. 6 ACF and PACF Plots of natural annual maximum streamflow of Karkheh River (d=0)

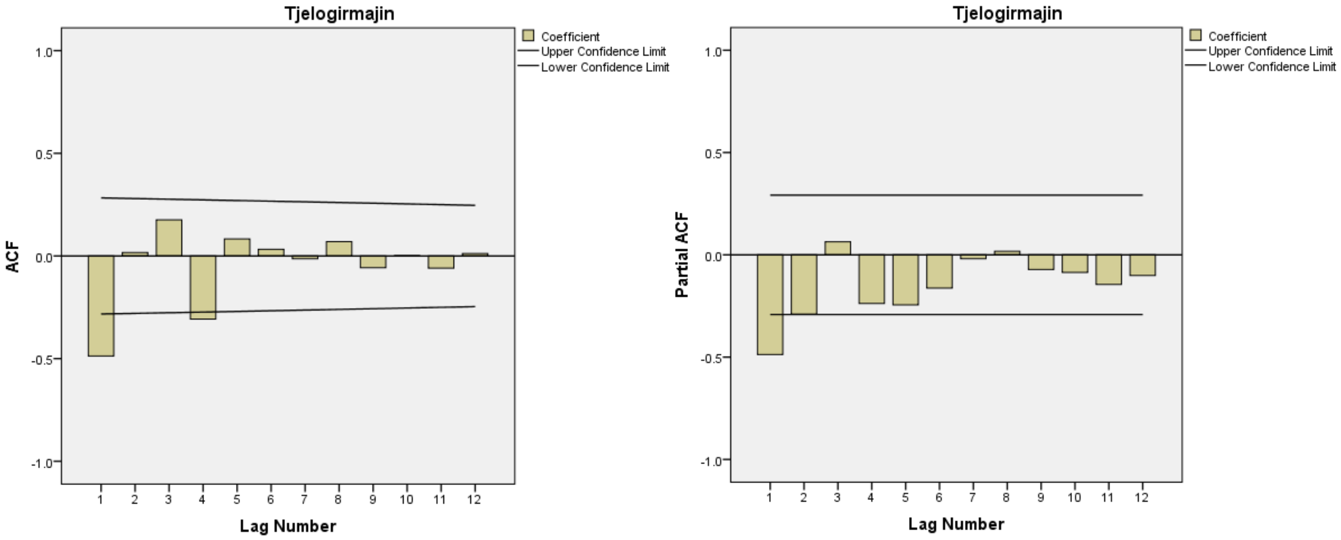

Fig. 7 ACF and PACF Plots of annual peak streamflow after one nonseasonal difference (d=1)

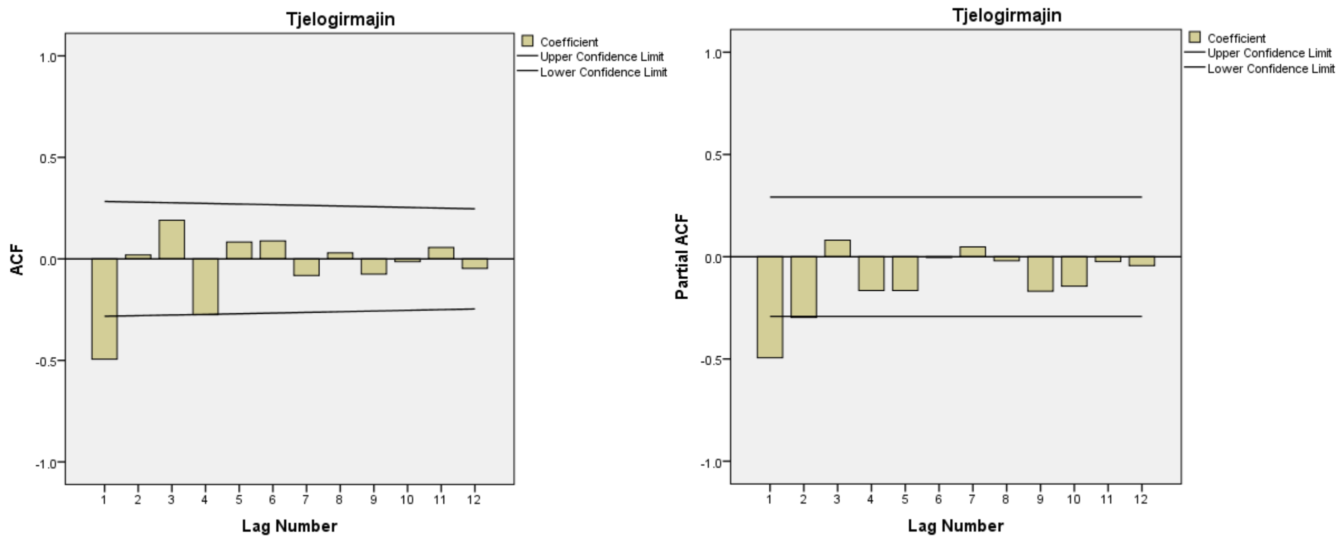

Fig. 8 ACF and PACF Plots of annual maximum streamflow after one nonseasonal difference (d=1)

C. Parameters Estimation

After the identification of model using the parameter estimation methods such as ML, CLS and ULS are done. The values of parameters estimation are shown in Tables I and II. The values of these tables showed that all the selected models are suitable for entrance to next stage because these selected models have two conditional stationary and invertibility. The AIC values are shown in Table V. The model that gives the minimum AIC is selected as best fit model. Obviously, model ARIMA(4,1,1) has the smallest values of AIC, then one would temporarily have a model ARIMA (4,1,1). The values of AIC for different ARIMA models are shown in Table V (AIC=88.87 in CLS estimation method for annual peak streamflow and AIC=77.75 in ML estimation method for annual maximum streamflow). In this case, the initial suggested model structure has the minimum AIC value and has been chosen as best model structure for annual extreme streamflow time series.

D. Diagnostic Check

In the Box Jenkins methodology, after selecting suitable model and estimated of parameters, the residuals of the model must requires examining to verify that selected model is an appropriate one for the series. An appropriate model should have uncorrelated residuals. This is the minimal condition for select of the best model. For a good predicting model, the residuals of the model must satisfy the requirements of a white noise process. Two common tests for this purpose are summarized briefly in the following paragraphs.

E. Port Manteau Lack of Fit Test

The goodness of fit of the selected model was tested using the Ljung-Box statistic test. The test is employed for checking independence of residual. From Tables III and IV, the goodness of fit values for the auto-correlations of residuals from the model up to lag 24 was ≥ 0.05. The result of Port Manteau test demonstrates the acceptation of the null hypothesis of model sufficiency at the 5% significance level and the set of autocorrelation of residuals was considered white noise. Since the model diagnostic tests show that all the parameter estimates are significant, and the residual series is white noise, the estimation and diagnostic checking stages of the modelling process are complete.

F. ACF and PACF of Residuals

The ACF and PACF of residuals of the model ARIMA (4,1,1) are shown in Figs. 9 and 10. Most of the values of the RACF and RPACF of residuals of the model lies within confidence, and figures do not indicate significant correlation between the residuals of model. The results of the ACF and PACF plots of the residuals and Port Manteau lack of fit test suggested that the residuals are white noise, therefore the ARIMA (4,1,1) model is the best model for forecasting of study series

G. Forecasting

ARIMA model can also be used for forecasting future values based on the historical data. The ARIMA (4,1,1) model was tested for its validity to forecast ten observations obtained for the years 2006−2015 for Karkheh River. The result of comparison between forecasted and observation data is shown Figs. 11 and 12. The observed streamflow was found to be closely aligned to the forecasted values. In order to evaluate the performance of the models, ten years ahead forecasts were generated for the testing period from 2006 to 2015 in Table VI. The hydrograph between observation and forecasted streamflow data using ARIMA models is shown in Figs. 11 and 12. These corresponding observed values are also shown in Figs. 13 and 14. The agreement between the observed and forecasted values is very good (R^2=0.84 for annual peak streamflow and R^2=0.87 for annual maximum streamflow), it is confirmed that the ARIMA (4,1,1) model is adequate. Also, this model is better than other models because ARIMA model gives low value of error and in good fit with the observed data.

TABLE I
VALUES OF NONSEASONAL ARIMA MODEL PARAMETERS FOR ANNUAL PEAK STREAMFLOW

Estimation Method	Type (Order) and Values of parameters ARIMA(p,1,q)	Absolute Value of t	Probability of t	Stationary Condition	Invertibility Condition
ML	P(1) = -0.48656	-3.81	0.0001	Satisfy	
	Q(0)				
CLS	P(1) = -0.48713	-3.78	0.0005	Satisfy	
	Q(0)				
ULS	P(1) = -0.49708	-3.88	0.0003	Satisfy	
	Q(0)				
ML	P(1) = 0.10744	0.66	0.5104	Satisfy	
	Q(1) = 0.93539	10.87	0.0001<		Satisfy
CLS	P(1) = 0.11274	0.69	0.4926	Satisfy	
	Q(1) = 0.96723	15.99	0.0001<		Satisfy
ULS	P(1) = 0.12820	0.84	0.4072	Satisfy	
	Q(1) = 0.99998	3.35	0.0001<		Not Satisfy
ML	P(4) = -0.3317	-2.25	0.0243	Satisfy	
	Q(1) = 0.86679	9.89	0.0001<		Satisfy
CLS	P(4) = -0.33489	-2.19	0.0339	Satisfy	
	Q(1) = 0.86679	13.48	0.0001<		Satisfy
ULS	P(4) = -0.36065	-2.4	0.0208	Satisfy	
	Q(1) = 0.89524	11.84	0.0001<		Satisfy

TABLE II
VALUES OF NONSEASONAL ARIMA MODEL PARAMETERS FOR ANNUAL MAXIMUM STREAMFLOW

Estimation Method	Type (Order) and Values of parameters ARIMA(p,1,q)	Absolute Value of t	Probability of t	Stationary Condition	Invertibility Condition
ML	P(1) = -0.51759	-4.14	0.0001<	Satisfy	
	Q(0)				
CLS	P(1) = -0.49304	-3.84	0.0004	Satisfy	
	Q(0)				
ULS	P(1) = -0.52951	-4.23	0.0001	Satisfy	
	Q(0)				
ML	P(1) = 0.14873	0.86	0.3922	Satisfy	
	Q(1) = 0.92809	8.16	0.0001<		Satisfy
CLS	P(1) = 0.230274	1.46	0.1501	Satisfy	
	Q(1) = 0.97512	28.55	0.0001<		Satisfy
ULS	P(1) = 0.17543	1.13	0.2631	Satisfy	
	Q(1) = 0.99999	3.35	0.0016		Not Satisfy
ML	P(4) = -0.26820	-1.71	0.087	Satisfy	
	Q(1) = 0.74897	6.36	0.0001<		Satisfy
CLS	P(4) = -0.26824	-1.7	0.0964	Satisfy	
	Q(1) = 0.69253	5.76	0.0001<		Satisfy
ULS	P(4) = -0.27556	-1.66	0.1031	Satisfy	
	Q(1) = 0.85681	8.77	0.0001<		Satisfy

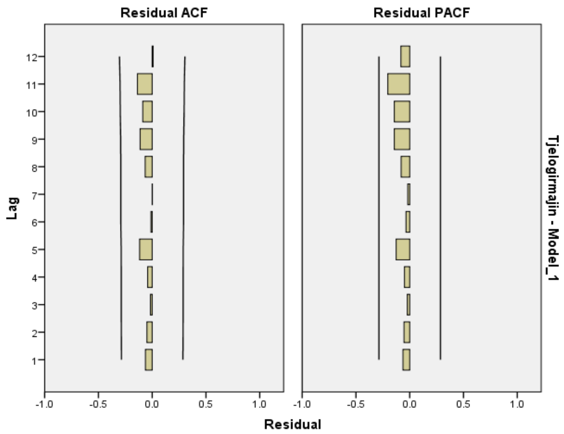

Fig. 9 ACF and PACF Plots for ARIMA (4,1,1) Residuals for annual peak streamflow

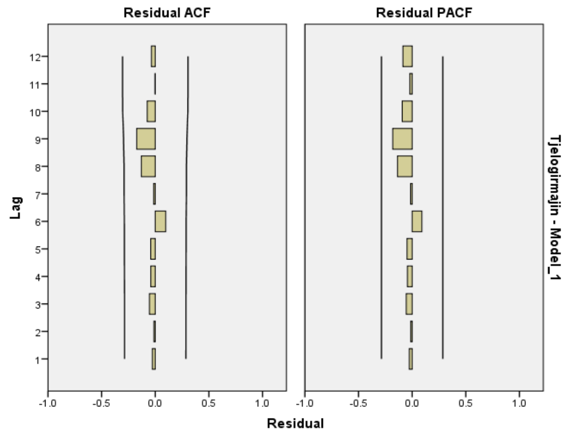

Fig. 10 ACF and PACF Plots for ARIMA (4,1,1) Residuals for annual maximum streamflow

TABLE III
RESULT OF AUTOCORRELATION CHECK OF RESIDUALS ANNUAL PEAK STREAMFLOW

ARIMA Model	Estimation Method	To Lag	Df	Chi-Square	Pr>Chi Square	Adequacy for Modelling
ARIMA(1,1,0)	ML	6	5	9.99	0.0754	Satisfy
		12	11	11.25	0.4228	
		18	17	14.32	0.6447	
		24	23	17.26	0.7962	
	CLS	6	5	9.68	0.0850	Satisfy
		12	11	10.94	0.4484	
		18	17	14.02	0.6659	
		24	23	16.93	0.8128	
	ULS	6	5	10.02	0.0748	Satisfy
		12	11	11.29	0.4190	
		18	17	14.38	0.6400	
		24	23	17.33	0.7928	
ARIMA(1,1,1)	ML	6	4	5.32	0.2562	Satisfy
		12	10	5.93	0.8212	
		18	16	9.21	0.9046	
		24	22	12.45	0.9473	
	CLS	6	4	4.63	0.3269	Satisfy
		12	10	5.20	0.8775	
		18	16	8.26	0.9409	
		24	22	10.89	0.9763	
ARIMA(4,1,1)	ML	6	4	1.30	0.8608	Satisfy
		12	10	2.77	0.9863	
		18	16	7.46	0.9653	
		24	22	10.70	0.9787	
	CLS	6	4	1.36	0.8504	Satisfy
		12	10	2.98	0.9818	
		18	16	7.56	0.9610	
		24	22	10.41	0.9822	
	ULS	6	4	1.25	0.8702	Satisfy
		12	10	2.53	0.9904	
		18	16	7.61	0.9596	
		24	22	11.47	0.9674	

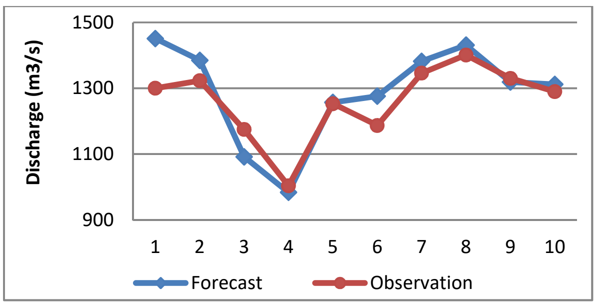

Fig. 11 Comparison of observed data and ARIMA (4,1,1) model annual peak streamflow (2006-2015)

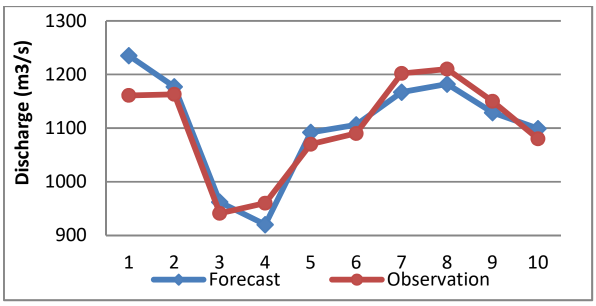

Fig. 12 Comparison of observed data and ARIMA (4,1,1) model annual maximum streamflow (2006-2015)

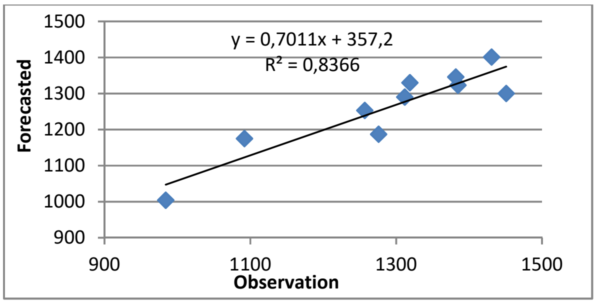

Fig. 13 Correlation between observation and forecasted values of annual peak streamflow

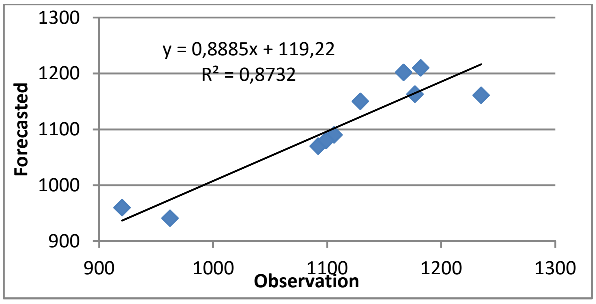

Fig. 14 Correlation between observation and forecasted values of annual maximum streamflow

TABLE IV
RESULT OF AUTOCORRELATION CHECK OF RESIDUALS ANNUAL MAXIMUM STREAMFLOW

ARIMA Model	Estimation Method	To Lag	Df	Chi-Square	Pr>Chi Square	Adequacy for Modelling
ARIMA(1,1,0)	ML	6	5	9.63	0.0866	Satisfy
		12	11	10.85	0.4559	
		18	17	14.10	0.6602	
		24	23	21.24	0.5665	
	CLS	6	5	8.87	0.1145	Satisfy
		12	11	10.14	0.5177	
		18	17	13.26	0.7185	
		24	23	20.50	0.6118	
	ULS	6	5	9.65	0.0856	Satisfy
		12	11	10.89	0.4525	
		18	17	14.21	0.6519	
		24	23	21.26	0.5653	
ARIMA(1,1,1)	ML	6	4	3.85	0.4262	Satisfy
		12	10	5.64	0.8445	
		18	16	10.50	0.8391	
		24	22	17.76	0.7201	
	CLS	6	4	4.15	0.3856	Satisfy
		12	10	5.74	0.8365	
		18	16	10.06	0.8637	
		24	22	16.58	0.7861	
ARIMA(4,1,1)	ML	6	4	1.22	0.8752	Satisfy
		12	10	5.29	0.8712	
		18	16	10.91	0.8152	
		24	22	15.22	0.8527	
	CLS	6	4	0.97	0.9139	Satisfy
		12	10	6.01	0.8144	
		18	16	11.58	0.7726	
		24	22	15.57	0.8364	
	ULS	6	4	2.15	0.7077	Satisfy
		12	10	6.91	0.7338	
		18	16	13.12	0.6638	
		24	22	17.33	0.7449	

IV. CONCLUSION

In this paper, stochastic model known as nonseasonal ARIMA was used to simulate and forecast annual extreme streamflow for Karkheh River at Iran. ARIMA model has the best fits of the criteria and the requirement. By analyzing of the predicted values in future, it was found that use of ARIMA model for predicting annual extreme streamflow is very good. The stochastic ARIMA models to annual streamflow time series could result in a better tool which can be used for water resource planning in studied region. ARIMA model has the ability to predict accurately the future annual extreme streamflow, especially short-term period, for all streamflow gauge stations in Karkhe River in Karkheh basin at Iran. The choice of model type itself has an important role in stochastic hydrology for forecasting and data generation, and each case deserves an investigation to determine the most appropriate model.

The significant ACF and PACF plots with high order in ARIMA (4,1,1) model (four order) can be caused by factors such as the good vegetation of the region and snowmelt. The good vegetation of the region and the forest causes water retention in the soil surface layer and delay in the rise in surface runoff. As well as vegetation reduces the power and erodibility destroyed by a severe storm (intense rain events happening across the region). Also, runoff from the storm drainage system seems to cause significant delays. The ARIMA model is suitable for short term forecasting because the ARMA family models can model short term persistence very well. The auto regressive model is a finite memory model, thus it does not fare well in long term forecasting.

TABLE V
GOODNESS OF FIT STATISTIC FOR ANNUAL PEAK AND MAXIMUM STREAMFLOW

Parameter	ARIMA Model	Estimation Method	Akaikc's Statistic
Annual Peak Streamflow	(1,1,0)	ML	103.4247
		CLS	103.4469
		ULS	103.4316
	(1,1,1)	ML	95.2824
		CLS	93.1350
	(4,1,1)	ML	90.8381
		CLS	***88.8680***
		ULS	91.0387
Annual Maximum Streamflow	(1,1,0)	ML	84.185
		CLS	84.9952
		ULS	84.1939
	(1,1,1)	ML	79.7781
		CLS	79.6182
	(4,1,1)	***ML***	***77.7478***
		CLS	78.8943
		ULS	78.1438

TABLE VI
FORECASTS AND OBSERVATIONS OF ANNUAL STREAMFLOW FROM PERIOD 2006-7 TO 2015-16

Period	Annual Peak Streamflow		Annual Maximum Streamflow	
	Forecast	Observation	Forecast	Observation
2006-7	1451	1300	1235	1161
2007-8	1385	1323	1177	1163
2008-9	1092	1175	962	941
2009-10	984	1004	920	960
2010-11	1257	1253	1092	1070
2011-12	1276	1187	1106	1090
2012-13	1382	1346	1167	1202
2013-14	1431	1401	1182	1210
2014-15	1319	1330	1129	1150
2015-16	1312	1290	1099	1080

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