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# TIME SERIES MODELING OF TROPICAL RIVER RUNOFF

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## Abstract

Rainfall and runoff phenomenon is a chaotic and complex outcome of nature which requires sophisticated modeling and simulation methods for explaination and use. Time Series modeling allows runoff data analysis and can be used as forecasting tool. In the present study an attempt is made to model river runoff data and predict the future behavioral pattern of tropical river based on monthly past observations. The runoff analysis and forecast are done using autoregressive integrated moving average (ARIMA) model. Selection of parsimon ARIMA model has shown good agreement of forected runoff values with the real time river runoff. In order to evaluate the prediction efficiency, we made use of statistical formulae applicable to hydrological events.

**INTRODUCTION**

Human civilization has rendered various attempts to control flood episode, but only a little success is evident. In the past, the emphasis was on the structural measures since these are very effective in flood control under normal conditions but are site specific and consume huge resources (man / machine power, material and time). Dams and reservoirs have, through the ages, provided tremendous social and economic benefits to mankind (water supply, irrigational, hydroelectric power generation etc.) despite prevention of flood. However, in recent years, the value of dams to human society has been questioned (Halwiindi, 2009) in view of a long history of unsatisfactory management in flood control structure. Therefore, recent trends are to emphasize on non-structural measures for an efficient flood management e.g. training, research, development activities etc.. Now a day's flood risk management systematically covers all actions for feasible and financially affordable prevention & protection of people and goods at risk, & conservation of environment & riparian ecology.

Rainfall and runoff (flood) forecasting are gaining more importance as now a days flood events are more frequent and intense in many countries around the world (Palmer and Raisanen, 2002). The process of estimating the future stages of flood flows and its time sequence at selected vulnerable points along the river course is called "Real Time Flood Forecasting" (Brath, 1999), is an effective non-structural measure for flood management. This could be carried out by estimation of flood, well in advance to provide sufficient lead time to the authorities to decide over the flood management issues. The flood forecast specifies the trends of river level (rising or falling) and the quantum of runoff (low / medium / high) to assess the likely loss of property and life (Singh and Woolhiser, 2000).

In the past, the main assumption in design of flood forecasting model types was about the linear association of influencing parameters. Linear forecasting methods such as Conceptual, Physical, Statistical approaches are unable to identify complex characteristics due to the goal of characterizing all time series observations, the necessity of time series stationarity and, the requirement of normality and independence of residuals (Povinelli, 1999). In case there is no proof of existence of chaos (non chaotic systems), other methods targeted towards deterministic or stochastic time series analysis can be applied with greater success (Damle, 2005).

**BACKGROUND**

Earlier the time series study of rainfall runoff process composed of synthesis of available annual hydrologic data in time dependent or independent stochastic components and identification of trends and cycles Matalas (1963) and Yevjevich (1972).. The simplest time series model that deals with one type of data only have three components to describes stochastical process linearly that is the Autoregression (AR), Integration (I) and Moving Average (MA) to combine as Autoregressive Integrated Moving Average (ARIMA) model (Box and Jenkins, 1970). The various linear and dynamic regression derivatives of ARIMA process are developed in terms of Periodic, Seasonal Deseasonalized (discrete), Exogenous input, Non linear regression, Multiple linear regression and Variation of average models and are abbreviated as PARIMA, SARIMA, DARIMA, ARMAX, NRL, MLR, and VARMA respectively models (McKerchar and Delleur, 1974; Hipel et al., 1977; Salas et al., 1980; Chang et al., 1984; Haltiner and Salas, 1988; Mishra et al., 2004; Wang, 2006). These models have been applied since long time in the modeling of rainfall runoff and forecasting stream flow and flood (Noakes et al., 1985; Salas, 1992; Bender and Simonovic, 1994 and Hipel and McLeod, 1994; María et al., 2004).

Graupe et al. (1976) used ARIMA model for simulating flow in Karstic basins. Kumar (1980); and O'Connell (1980) used time series to forecast flood episode consequent of rainfall occurrence. Chang and Tiao (1985) and Weeks and Boughton (1987) attempted an accurate flood forecast systems using time series methods. Chiew et. al., (1993) and Cheng (1994) tried ARIMA to forecast rainfall runoff at different catchments of varying scales. Maidment (1993) suggested use of the periodic PAR, PARMA and periodic Gamma autoregressive (PGAR) models for single and multiple periodic time series. Broesen (2008) developed time series analysis software ARMASA.

Hsu et al., (1995) first compared ARIMA method with artificial neural network method. Later Zhang and Govindaraju (2000); Young et.al., (2002); Cigizoglu, (2003); Sana et al. (2003); Organ and Yalcin (2004); Smith (2005); Kisi, (2005); and DeSilva (2006) have attempted time series analysis with the inclusion of new mathematical approaches based on non linear concepts and with artificial intelligence methods of forecasting. Naill and Momani (2009) and Volkan and Onkur (2010) mixed time series models with other mathematical models to devise new approaches.

**METHOD**

In this study an attempt is made to forecast tropical river runoff using 10 years monthly average data. The univariate time-series modeling approach Box et al. (1994) for the prediction of next time ahead forecasting is very practical and versatile for observations having more or less linear trends. Box Jenkins approach makes use of three (3) linear filters: the autoregressive, the integration, and the moving average filter. The general ARIMA equation is given as:

$$(\phi\ (B))y_t = (\theta(B))a_t \qquad (1)$$

An expansion of general form of a non seasonal univariate model is structurally described by

$$(1-\phi_1 B-\phi_2 B^2-.....-\phi_p B^p)y_t=(1-\theta_1 B-\theta_2 B^2-......-\theta_q B^q)a_t \qquad (2)$$

Where

$y_t$ - Stationary series after differencing = $(1-B)^d Y_t$

$Y_t$ - The input variable with reference to time

d - The number of non seasonal differencing

Φ and θ – The non seasonal autoregressive and moving average term's order p and q respectively.

B –The Backward shift operator, define as Bzt = $z_{t-1}$

$a_t$ – The residual (white noise term)

The order p and q of autoregressive and moving average terms can be determined by examining the autocorrelation function (ACF) and partial auto-correlation function (PACF) graphs. The three-stage standard modeling procedure (identification, estimation, and diagnostic check) was used to develop time series models. For complex time series having regular patterns of seasonal changes can be modeled using seasonal ARIMA i.e. SARIMA model as detailed in Vandaele (1983). Minitab-15, softwaew is used for model development.

**STUDY AREA**

In this study the river runoff of a perennial medium size hilly river named Kulfo is modeled. The river originates in the tropical region from the highland & ridges of Haringa, Kecha & Tiba in Ethiopia. The Kulfo River spans in great Abaya - Chamo basin. The river catchment area is about 16,400 $km^2$ and river drain area is about 3500 $km^2$. The Kulfo River is mainly utilized for irrigation and public consumption. The river runoff data is collected at ArbaMinch gauge station close to its destination point at Abhaya lake.

**RESULTS AND DISCUSSIONS**

**Statistical Analysis of River Runoff Data:** The twenty (20) years time series plot of Average Monthly Rainfall and Runoff (year 1977-1986) of Kulfo River is plotted in the fig. 5.1, it shows the time dependent quantitative variations and the patterns of the rainfall and associated runoff. A marked rise is obvious in the figure 5.1 in the mean rainfall as well as in river runoff after the year 1986.

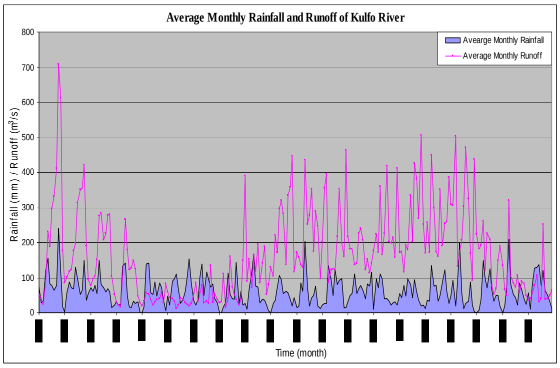


**Figure 1 Rainfall and Runoff of Kulfo River**

The histogram and normal frequency distribution curve of river runoff is shown in fig. 5.2. Obviously the 20 years runoff frequency distribution is not in normal shape and there exists few extremes runoff events (both low and high) which all fall outside the normal distribution curve. However in the two decades the high flow events are lesser than deficient flow episodes.

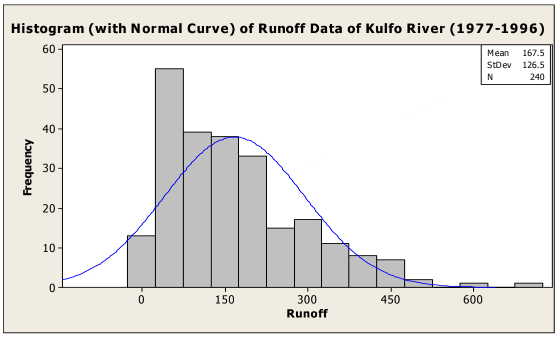


**Figure 2 Histogram and Frequency of Runoff**

The descriptive statistics of river runoff data is presented in table 5.1. There is a vast variation in the minimum and maximum runoff values. However, the mean runoff too is towards lower side indicating a deficient runoff during most of the time. A comparison of mean and Median values indicates the total shift of data either towards lower end of mean. Coefficient of Variation measures relative variability and the dispersion of runoff with its mean. The standard deviation indicates a little spread of runoff values out from the mean. Nearly equal and lower values of Standard Error of Mean (SE Mean) and less standard deviation indicates a precise estimation of data. Small values of skewness and kurtosis are indicative of concentrated and nearly centralized data close to mean.

**Table 1 Descriptive Statistics of Runoff Data**

| SN | Statistical Parameters | Values |
|---|---|---|
| 1 | Total variable | 240 |
| 2 | Minimum | 11.81 |
| 3 | Maximum | 708.54 |
| 4 | Mean | 167.52 |
| 5 | Std. Error of Mean | 8.16 |
| 6 | Median | 141.77 |
| 7 | Standard Deviation | 126.49 |
| 8 | Coef. of Variation | 75.51 |
| 9 | First Quartile Q1 | 57.93 |
| 10 | Third Quartile Q3 | 225.85 |
| 11 | Skewness | 1.12 |
| 12 | Kurtosis | 1.28 |

A box plot and individual value plot (fig.–5.3 and 5.4) are used to illustrate non parametric distribution of runoff data i.e. the quartile information, the grouping of numerical data and a graphical summary of data distribution including its shape, central tendency, and variability. The box represents the inter-quartile range (the middle 50% of the data). In the box plot the top line i.e. the third quartile indicates that 75% of the data are less than or equal to

200 $m^3/s$ runoff value; the middle box represents that 50% of the data are contained within and the bottom line i.e. the first quartile shows that 25% of the data are less than or equal to its value. The box plot also displays Outlier Observation beyond its upper or lower whisker.

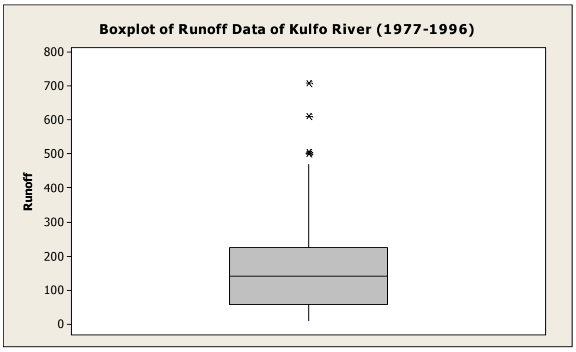


**Figure 3 Box Plot Runoff Data of Kulfo River**

The Individual plot of runoff data of Kulfo river helps in identification of the extreme values and helps in the possible grouping of runoff values. Individual RR graph of duration 1977-1996, shows the range of river runoff that is available continuously and also with the decline frequency.

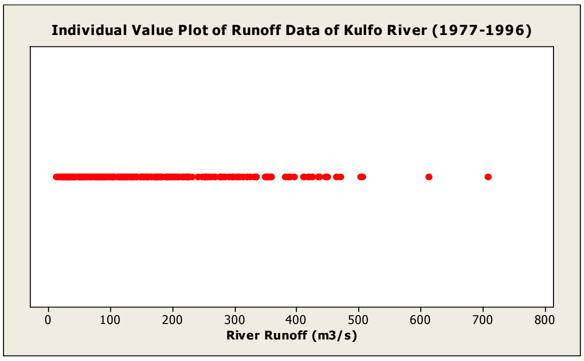


**Figure 4 Individual value plot of River Runoff**

**Development of Stochastic Univariate Time Series Model:** In tropical region, rainfall and runoff are more a cyclic process than seasonal one. ARIMA can be used to model patterns that may not be visible in plotted data. For identification of order of ARIMA model parameters (p, d, q, P, D, Q and s), the Auto correlations coefficient (ACC) and Partial autocorrelations coefficient (PACC) of runoff time series are plotted for various combinations of differencing (d=0 and d=1) and lags (N / 4, N=Numbers of observations). The identified parameters are then evaluated and used for development of forecasts. The residuals are worked out during the model validation stage by subtracting the observed runoff by the forecasted one. For a best fit ARIMA model the residual values must be around zero or negligible. The following plots (fig. 5.5) are used to examine the model's goodness of fit.

**(a) Normal Probability Plot of residuals:** For a fit model results the residual points form a straight line. Any head of from the straight line indicate depart from the normality assumption and scope for further model improvements.

**(b) Residuals Vs Fitted Values:** This plot shows a random pattern of residuals on both sides of 0. If a point lies far from the majority of points, it is an outlier. The Residual plot should be patternless.

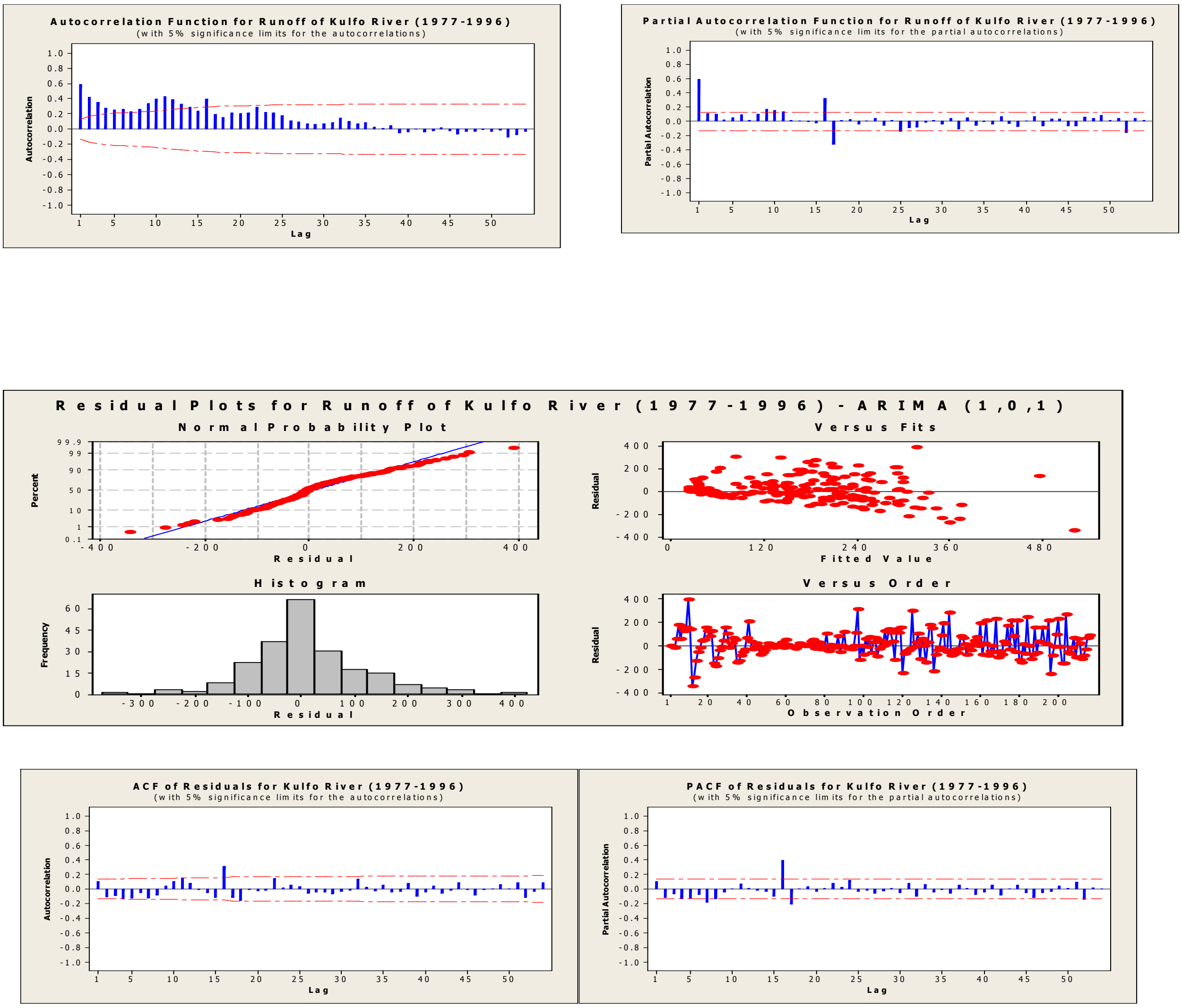


**Figure 5 Univariate ARIMA Model Development Process for Kulfo River (1977-1996)**

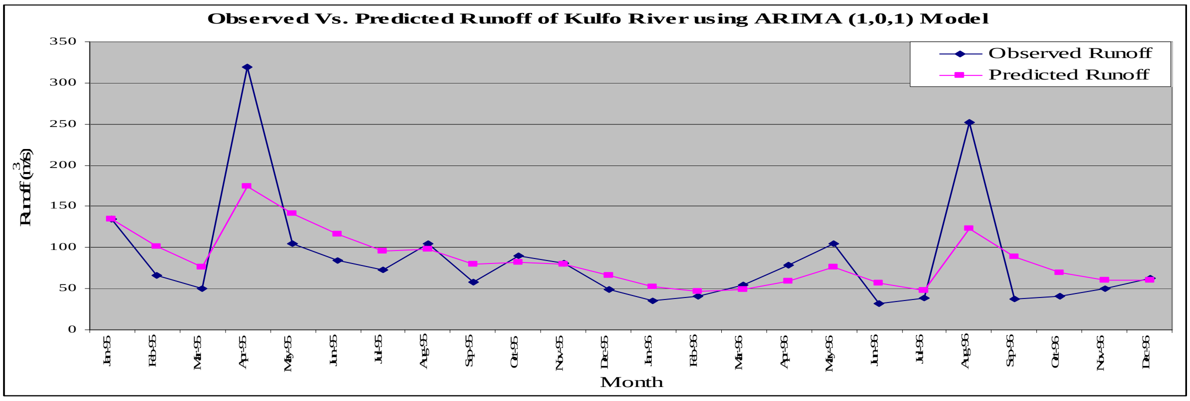


**Figure 6 Univariate ARIMA Model Forecasts for Kulfo River (Jan.-Dec., 1995-96)**

**(c) Histogram of the Residuals:** This shows the general characteristics of the residuals including typical values, spread, and shape. A long tail on one side indicates a skewed distribution.

**(d) Residuals Versus Order of Data:** This plot of all residuals in the order, can be used to find non-random error of time-related effects. This plot is to recognize whether residuals are uncorrelated.

**(e) ACC and PACC of Residuals:** This plot helps in final decision about the best fit and optimum applicability of fitted model. For an ideal ARIMA model fit the values of ACC and PACC should show a random pattern on both sides of 0. A non-random pattern violates the assumption that predictor variables are unrelated to the residuals.

In fig. 5.5 the ACC and PACC graph are plotted to decide the order of parameter p, d and q. A few trials of different combination of p and q are done and satisfying the parsimony requirement (model selection with least value parameters), a final ARIMA (1,0,1) model without any differencing requirement, is selected for forecasting. The runoff pattern does not show any seasonal pattern this fact is also palpable in the ACC and PACC plots.

Subsequent to model development the runoff forecasts are done for two year period of January to December 1995-96 and are plotted against the observed runoff in fig. 5.6. From the runoff forecast graph it is obvious that the model depicts a good agreement with the runoff pattern however, runoff quantities are over predictive during the low flow periods and underestimated when high runoff conditions prevails. Considering the quantitative results of runoff forecasts the model is reasonably well for moderate runoff forecasts. Model is good enough to capture trends during high runoff but fall short for satisfactory estimation of flow. Obviously the error in forecast decreases with the reducing runoff values. The residual analyses of model forecasts are consistent to the requirement of a perfect fit model. Therefore, ARIMA (1,0,1) model is strongly recommended for long term predictions of mean monthly runoff of the Kulfo river.

**5.3 Model Performance Measures and Efficiency Criteria:** The performance measures and efficiency criterion mathematically evaluates the degree "how well a model simulation fits the available observations" (Beven, 2001). It is observed that river runoff rapidly rises when there is precipitation, quickly decreases after the rain ends, and (asymptotically) slowly decreases long after precipitation ends due to baseflow i.e. a runoff event is governed by above three stages of river inflow. Thus models can only be confirmed or evaluated by the demonstration of good agreement between several sets of observations and predictions. The above discussion also implies need of using multiple performance measures over a single measure (Yapo et al., 1998; Boyle et al., 2000). The following performance measures are used to judge the performance of stochastic model:

1. Coefficient of Correlation

$$R = \frac{\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2 (P_i - \overline{P})^2}}$$

2. The Coefficient of Determination (CD) **/** *Pearson's R* **squared** ($R^2$),**:**

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2 \sum_{i=1}^{n}(P_i - \overline{P})^2}}\right]^2$$

3. Nash-Sutcliffe efficiency **(**E):

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O_i})^2}$$

4. Index of Agreement (d):

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i^{'} - O_i^{'})^2}{\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2} = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2}$$

where $P_i^{'} = P_i - \overline{O}$ and $O_i^{'} = O_i - \overline{O}$

5. Relative efficiency criteria (Erel and drel)

$$E_{rel} = 1 - \frac{\sum_{i=1}^{n}\left(\frac{O_i - P_i}{O_i}\right)^2}{\sum_{i=1}^{n}\left(\frac{O_i - \overline{O}}{\overline{O}}\right)^2} \qquad d_{rel} = 1 - \frac{\sum_{i=1}^{n}\left(\frac{O_i - P_i}{O_i}\right)^2}{\sum_{i=1}^{n}\left(\frac{|P_i - \overline{O}| + |O_i - \overline{O}|}{\overline{O}}\right)^2}$$

6. Fractional Bias (FB):

$$FB = \frac{2(\overline{O} - \overline{P})}{(\overline{O} + \overline{P})} \qquad \text{where } \overline{O} = \frac{\sum_{i=1}^{n} O_i}{n} \text{ and } \overline{P} = \frac{\sum_{i=1}^{n} P_i}{n}$$

Most of the efficiency criteria contain a summation of the error term (difference between the simulated and the observed variable at each time step) normalized by a measure of the variability in the observations. The following errors are computed to assess the model capabilities:

**Mean Bias Error (MBE) and Mean Absolute Error (MAE):** IS TO ASSESS AVERAGE ERROR OR AVERAGE MODEL BIAS (UNDER OR OVER PREDICTION) BY KNOWING THE level of overall agreement between the observed and modelled datasets without omission of the signs of the errors. The summation of the absolute or squared errors is used to avoid the canceling of errors of opposite sign and thus emphasizing on larger errors and neglecting the smaller errors.

**Root Mean Squared Error (RMSE) and Normalised Mean Square Error (MMSE):RMSE** DENOTES AVERAGE MODEL PREDICTION ERROR WITH no upper bound and NMSE is a measures of mean relative scatter and reflect random errors.

$$ME\ (MBE) = \frac{\sum_{i=1}^{n} e_i}{n} = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n} = \overline{P} - \overline{O}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_i|$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}|e_i|^2}{n}} = \sqrt{\frac{\sum_{i=1}^{n}|(P_i - O_i)|^2}{n}}$$

$$NMSE = \frac{\overline{(O - P)^2}}{\overline{O}\overline{P}}$$

**Table 2**

**Performance Measures and Errors**

| Measures | Standard values | Model Value |
|---|---|---|
| CC | 1 | 0.79 |
| CD | 1 | 0.63 |
| E | 1 | .54 |
| d | 1 | .77 |
| Erel | 1 | .65 |
| drel | 1 | .83 |
| FB | 0 | 0.007 |
| MBE | 0 | -0.31 |

| | | |
|---|---|---|
| MAE | 0 | 28 |
| RMSE | 0 | 45.3 |
| NMSE | 0 | 0.23 |

In an under estimate model errors should be in order of MBE ≤ MAE ≤ RMSE that is true in this study. A detailed description of above statistical formulae is attainable from any statistical book and the relative usefulness is discussed at Rashmi (2012). Despite the large difference in observed and forecasted values during the month of April, 1995 and August 1996, the overall performce of fitted model is about 75% satisfaction level. Therefore, the fitted model is an excellent one for the forecasting purposes.

**CONCLUSION**

From the forecast graph (fig. 5.5) it is obvious that the trends of runoff are nicely captured in terms of average values. However, the forecasts are insensitive to tune with the extreme variations in runoff. Thus the performance of fitted ARIMA model is well for runoff simulation in the mean levels having less irregular and sharp nodes.

The high runoff peaks are the results of abrupt precipitation and / or sudden contribution from the catchment area or tributaries. The maintainability of substantial amount of runoff in the river can also be attributed to long lasting base flow and storage release etc. These features give rise to a non linear and complex runoff pattern which is mostly non-uniform and thus difficult to capture through ARIMA process. Therefore ARIMA model did not well envelop both the high and low values of runoff and vacillate to provide a reasonable quantification of runoff during odd or unusual river flow circumstance. However, these models could be exploited to have an idea about the upcoming events of abrupt changes in runoff conditions. However, the forecast efficiency can be improved by application of finer resulation of the data. The fitted model is recommended for flood warning use.

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