RESEARCH PAPER International Journal of Agricultural Engineering | Volume 7 | Issue 1 | April, 2014 | 142–148

Application of temporal disaggregation model for Tungabhadra river in stream flow generation

MALLIKARJUNA AND **A.A. ATRE**

Received : 04.12.2013; **Revised :** 13.02.2014; **Accepted :** 25.02.2014

See end of the Paper for authors' affiliation

Correspondence to :

MALLIKARJUNA
Department of Soil and Water Conservation Engineering, Dr. A.S. College of Agricultural Engineering, Mahatma Phule Krishi Vidyapeeth, Rahuri, AHMEDNAGAR (M.S.) INDIA
Email : dandu431@gmail.com

ABSTRACT : The present study has been carried out to elaborate a model for generating the synthetic sequences of 10-daily stream flows for Tungabhadra river at Munirabad dam site. The parameters of autoregressive models intent by method of moment and maximum likelihood method in generating annual stream flow data. The goodness of fit of autoregressive model was tested by Akaike Information Criterion. The autoregressive model of order one was found best for generating annual stream flow data. Lane's condensed disaggregation model was selected to represents the 10-daily stream flows. Since, the disaggregation model for generating synthetic stream flows requires previously generated annual stream flow series, the annual stream flow series was modeled by using autoregressive model of order one. The annual stream flow discharges and 10-daily stream flow discharges of Tungabhadra river at Munirabad dam site for 33 years (1977-2009) were used for elaborating mathematical model. The comparison of statistical characteristics of historical and generated stream flows suggest that temporal disaggregation model can be used to generate 10-daily stream flow data which conserves the mean, skewness and kurtosis for some 10-daily stream flow along with the mean and kurtosis of aggregative annual stream flow.

KEY WORDS : Akanke information criterion, Temporal disaggregation model, Generation

HOW TO CITE THIS PAPER : Mallikarjuna and Atre, A.A. (2014). Application of temporal disaggregation model for Tungabhadra river in stream flow generation. *Internat. J. Agric. Engg.*, **7**(1) : 142-148.

The generation of synthetic series of stream flow data is generally needed for reservoir sizing, for determining the risk of failure of water supply for irrigation system, for determining the risk of failure of dependable capacities of hydroelectric systems, for planning studies of future reservoir operation and similar applications (Salas *et al.,* 1980). In the river basin studies the stochastic sequence of inflows and rainfall are used to determine how different system designs and operating policies might perform. Therefore, the study of reservoir operation system can employ various alternate stochastic hydrologic time series models to evaluate different scenario of water resources system operation. Since the rainfall and inflows are the important inputs to the water resources system, the development of good stochastic models is essential in order to determine an optimal system operation. The appropriate models that generate flow sequences are those, which manage to characterize the stream flows ideally representing the statistical and the correlation structure of the corresponding observed stream flows.

In hydrology, the generation of sequence of probabilistic variables like rainfall, stream flows etc. is realized to be a necessity and the field of operational hydrology covers this aspect. The stream flow data may be required in different forms like, daily, weekly, 10-daily, monthly, etc. Accordingly various stream flow forecasting models exist for generating the stream flow data of different intervals. Several types of model, such as autoregressive (AR), moving average (MA) and autoregressive moving average (ARMA) have been developed. Autoregressive moving average (ARMA) models have greater flexibility in fitting of time series than autoregressive (AR) models.

The stream flow data can be generated in two ways. In first type of generation, stream flows are generated directly. This is called direct generation and can be carried out where stationarity of stochastic process holds. The indirect generation has advantages as well as serious drawbacks. The length of available period is larger for rainfalls than for stream flows but the construction of rainfall stream flow transformation model itself is too complex. Hence in the present study, the sequential generation of stream flow is done by using the direct method. The direct generation model *i.e.* disaggregation model is used for stream flow generation. The present study was undertaken for the main objective of sequential generation of 10-daily stream flow of Tungabhadra river at Munirabad dam site using temporal disaggregation model.

METHODOLOGY

Site location and data acquisition:

The Munirabad dam on Tungabhadra river situated at Mallapur village in Bellary district is near to heritage site Hampi. The dam site is located at 15°15' N latitude and 76°21' E longitude. The catchment of the dam is characterized by hilly terrain with high to medium rainfall. The average temperatures of the place vary from 10°C to 40°C. The average rainfall of the area is 639 mm. The required reservoir level data at Munirabad dam site were obtained from the office of the Irrigation Central Zone, Bellary. The reservoir level data were converted to volume data in thousand million cubic feet (TMC) using tables provided for this purpose and then it was converted to discharge in cumec.

Estimation for annual autoregressive (AR) models:

Consider an available sample of annual stream flow data denoted by X_1, X_2, ..., X_N, where N is the number of years of data. In general let the normal sequence be represented by Y_1, Y_2, ..., Y_N, Which can be obtained by transforming the observed data X_t t=1, ...N. With this data sequence the parameters $\overline{X}$, S^2, $\varnothing_1$ ....$\varnothing_p$ and σ_ε^2 of the AR (p) model can be estimated. Determination of parameters of AR (p) model can be done by different methods like method of moment and maximum likelihood method.

Akaike information criterion (AIC):

A mathematical formulation which considers the principle of parsimony in model building is Akaike information criterion (AIC) proposed by Akaike (1974). AIC is used for checking whether the order of the fitted model is adequate compared with the other orders of the dependence model. The AIC for an AR (p) model is

$$\mathbf{AIC\,(p) = N\ln(\sigma_\varepsilon^2) + 2\,p} \tag{1}$$

where σ_ε^2 is the maximum likelihood estimate of the variance. Therefore, a comparison can be made between the AIC (p) and the AIC (p-1) and AIC (p+1). If the AIC (p) is less than both the AIC (p-1) and AIC (p+1), then the AR (p) model is best.

Ten-daily stream flow generation by temporal disaggregation:

Lane (1979) has developed an approach, which essentially sets to zero several parameters of extended model which are not important. The model equation may be written as

$$\mathbf{Y_2 = A_2\,X + B_2\,£ + C_2\,Y_{2-1}} \tag{2}$$

where

t is the current 10-daily stream flow being generated

A_τ, B_τ, C_τ are parameters.

Y is the column matrix of current 10-daily values being generated.

X is column matrix of current annual values.

The main advantage of this model is the reduction of the number of parameters.

Parameters estimation for the model equation:

The condensed model may be considered as a form of the extended model applied to 10-daily at a time. The parameters are estimated as:

$$\widehat{\mathbf{A}}_\tau = \left[\mathbf{S_{YX}\,(\tau,\tau) - S_{YY}\,(\tau\tau\tau-1)\,S_{YY}^{-1}\,(\tau-1,\tau-1)\,S_{YX}\,(\tau-1,\tau\tau)}\right]$$
$$\left[\mathbf{S_{XX}\,(\tau,\tau) - S_{XY}\,(\tau,\tau-1)\,S_{YY}^{-1}\,(\tau-1,\tau-1)\,S_{YX}\,(\tau-1,\tau\tau)^{-1}}\right] \tag{3}$$

$$\widehat{\mathbf{C}}_\tau = \mathbf{[S_{YY}\,(\tau,\tau-1) - \widehat{A}_\tau\,S_{XY}\,(\tau,\tau-1)]\,S_{YY}^{-1}\,(\tau-1,\tau-1)} \tag{4}$$

and

$$\widehat{\mathbf{B}}_\tau\,\widehat{\mathbf{B}}^{\mathbf{T}} = \mathbf{S_{YY}\,(\tau,\tau) - \widehat{A}_\tau\,S_{XY}\,(\tau,\tau) - \widehat{C}_\tau\,S_{YY}\,(\tau-1,\tau)} \tag{5}$$

where, S_{YY} is the matrix of covariance among 10-daily series.

S_{YX} is the matrix of covariance between 10-daily series and annual series.

S_{XX} is the matrix of covariance among the annual series.

S_{XY} is the matrix of covariance between the annual value series associated with current 10-daily and these values associated with the previous to the current 10-daily.

The required moment estimates are S_{YY} (τ, τ), S_{YX} (τ, τ), S_{XX}(τ, τ-1), S_{YX} (τ-1, τ). In order to estimate these moments consider.

$$\mathbf{X_v^{'} = X_v - \overline{X}} \tag{6}$$

where,

$X_v^{'}$ is the reduced annual series for N years

X_v is the observed annual series for N years

$\overline{X}$ is the mean of annual series

v = 1, 2, 3, ...N.

The seasonal reduced series is considered as:

$$\mathbf{Y_{v,\tau}^{'} = Y_{v,\tau} - \overline{Y}_\tau} \tag{7}$$

where,

$Y_{v,\tau}^{'}$ is the reduced 10-daily series for N years

$\overline{Y}_\tau$ is the mean of 10-daily series

$v = 1, 2, 3, \ldots\ldots N$

$\tau = 1, 2, 3, \ldots\ldots \omega$.

N is the number of 10-daily required for disaggregation in a year, for 10-daily data generation ω=6.

The covariances are estimated from observed data (Salas *et al.*, 1980) as follows:

$$S_{YY}(\tau, \tau) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},36 \end{bmatrix}\left[Y'_{v},1, \cdots\cdots Y'_{v},36\right] \quad (8)$$

$$S_{YX}(\tau, \tau) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},36 \end{bmatrix}\left[X'_{v}\right] \quad (9)$$

$$S_{YY}(\tau, \tau-1) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},36 \end{bmatrix}\left[Y'_{v},36,\ Y'_{v},1,\ Y'_{v},2 \cdots\cdots Y'_{v},35\right] \quad (10)$$

$$S_{YX}(\tau-1, \tau) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},36 \\ Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},35 \end{bmatrix}\left[X'_{v}\right] \quad (11)$$

$$S_{YY}(\tau-1, \tau-1) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},36 \end{bmatrix}\left[Y'_{v},36,\ Y'_{v},1,\ Y'_{v},2 \cdots\cdots Y'_{v},35\right] \quad (12)$$

$$S_{YY}(\tau-1, \tau) = \frac{1}{N}\sum_{v=1}^{N}\begin{bmatrix} Y'_{v},1 \\ Y'_{v},2 \\ \vdots \\ Y'_{v},36 \end{bmatrix}\left[Y'_{v},1,\ Y'_{v},2 \cdots\cdots Y'_{v},36\right] \quad (13)$$

$$S_{XX}(\tau, \tau) = \frac{1}{N}\sum_{v=1}^{N}\left[X'_{v}\right]\left[X'_{v}\right] \quad (14)$$

$$S_{XY}(\tau, \tau-1) = \left[S_{YX}(\tau-1, \tau)\right]^{T} \quad (15)$$

$$S_{XY}(\tau, \tau) = \left[S_{YX}(\tau, \tau)\right]^{T} \quad (16)$$

■ RESULTS AND DISCUSSION

The experimental findings obtained from the present study have been discussed in following heads:

Modeling of 10-daily stream flow series:

The modeling of 10-daily stream flow was performed by using Lane's condensed disaggregation model given equation (2). To generate the 10-daily stream flows, disaggregation model requires a previously generated annual stream flow series. The annual stream flow series was modeled by autoregressive model. Historical annual and 10-daily stream flows were used to estimate the parameters of disaggregation model. The AR (1) model of method of moments was used to estimate the parameters of disaggregation model. Firstly, the sample covariances were computed by using equations (8) to (16). Then, the parameters were obtained by using equations (3) to (5). The parameters of disaggregation model in matrix form different 10-daily are given in Table 1, 2 and 3.

Table 1 : Parameter A_2=(36x1) for 10-daily stream flow disaggregation model

-0.008
0.002
0.012
-0.013
-0.006
0.007
-0.002
0.011
-0.019
0.006
0.003
-0.010
-0.004
0.008
0.014
-0.001
-0.015
0.011
-0.005
0.000
-0.014
-0.010
-0.012
0.014
-0.006
-0.002
0.001
0.013
0.009
0.005
-0.017
0.018
-0.010
0.019
0.023
-0.013

Table 2 : Parameters Aτ (36x36) of 10-daily stream flow disaggregation model

-8.0	1.3	0.0	1.0	-0.2	-2.0	-0.5	0.4	0.3	-3.0	-2.5	-2.0	0.3	0.3	1.0	1.0	1.0	0.0	0.1	0.4	0.0	0.3	0.0	-0.5	2.0	-0.2	0.0	-0.8	-0.3	1.0	1.0	-3.0	0.0	-0.3	-2.0	-0.5
-1.1	0.0	0.0	-0.5	0.0	0.3	0.6	-0.2	-0.1	-0.1	-0.8	0.1	0.3	0.2	0.6	-0.3	2.3	0.2	0.0	-0.3	0.1	-0.6	0.0	-0.3	-0.9	0.0	-0.1	-0.7	0.3	-1.0	0.5	0.2	-0.4	0.3	-1.3	0.9
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.9	0.0	0.0	0.0	0.9	0.0	0.0	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.4	-0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0
0.0	0.6	0.0	-0.4	-0.2	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
0.0	0.6	0.1	0.4	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	-0.5	0.0	0.0	-0.1
0.0	-0.4	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0
0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.9
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0
0.0	0.0	-0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.9	0.0	0.0	0.1	0.0	0.0
0.0	0.0	0.0	0.0	-0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.3	0.0	0.0	0.0	-0.1	0.0
0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.9	0.0	0.0	-0.1	0.4	0.0
0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.7	0.0	0.4	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	-0.5	0.0	0.0	0.0
0.0	-0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	1.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.3	0.4
1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	0.0	1.0	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	-0.5
0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0
0.0	-0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.1	-0.3	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.4	0.1	0.0
0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1	-0.5	0.0	0.1
0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	1.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0
0.0	0.1	0.0	-0.2	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	-0.4
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
-0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
0.0	-0.1	0.0	0.1	0.0	0.1	0.0	0.0	-0.5	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	0.0
0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.3	0.0	0.0
0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.3	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	-0.1	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2

Table 3 : Parameters Bt (36x36)of 10-daily stream flow disaggregation model

-0	1.7	3.7	-2	4	4.8	-0	1.4	4.2	9.5	1.2	-2	3.9	1.2	2	-1.6	-2.2	1	0.43	-4.4	3	-2	-2	2.9	0.36	0	7.96	5.38	3.8	1.21	6.09	9.9	8.5	16	16	23
0	-0	-1	0.1	-1	-1	-0	-0	0.2	-1	0.5	0.39	-1	-0.8	-1.2	0.47	0.8	-0.2	0.27	0.7	0.3	0	1.4	-0.4	0.38	0.6	-1.6	-1	-1	-0.1	-0.1	-0.8	0.2	-3	-3.9	-6.1
0	-2	-4	-0	-2	-1	-1	-2	-1	-2	1.4	3.03	-1	-1.7	-3.2	3.18	2.72	-1	0.02	1.5	-3	-1	4.2	-1.2	-0.9	0.6	-5.7	-4.4	-6	-3.8	-4.1	-4.8	-2.9	-15	-14	-22
-0	0.7	1.7	0	2.9	2.2	-0	0.7	0.2	3.7	-0	0.24	0.1	0.7	0.6	-1.2	0.28	0.2	-1.1	-2.4	-0	-0	-2	2.2	-1.1	-0	0.73	1.91	0.8	1.26	1.93	1.9	1.6	6	8.5	6.1
0	-0	-2	-0	-4	-3	-1	0.1	4.2	-8	1.2	0.41	0.2	-2.8	1.2	1.26	-3.1	1.4	2.19	1.5	2.4	4.7	4.7	-8.8	4.04	-2.4	4.64	-3.4	-2	-1.8	-5.2	-10	-8.1	-2	-16	1.7
0	-0	-0	-0	-4	-5	-1	0.5	1	-13	1.3	-2.1	-1	-2.6	2.4	-0.7	-6.7	0.7	2.61	4	2.1	4.7	1.2	-11	5.47	-4.1	6.86	-3	0.7	-1.1	-6.9	-12	-11	-2	-15	8.7
0	-0	-1	-0	0.2	-1	-1	-0	0.2	-2	-0	0.63	0.1	-0.4	-0.7	0.48	-0.8	-0.6	0.18	0.1	-1	0.3	1.5	-1.3	-0.1	-0.6	-0.4	-2	-2	-1.5	-1.5	-3.1	-2.6	-3	-4	-2.5
0	-1	-2	0	-1	0.1	-0	-1	0.2	0.4	-1	1.31	-0	-0.3	-1.5	1.54	1.27	-0.6	-0.3	-0.1	-1	0.1	2.3	0.1	-0.6	1.1	-2.6	-1.7	-2	-1.4	-0	-0.1	0.6	-4	-3.8	-8.9
0	-1	-3	0	-1	1.2	0.3	-1	-0	3.1	2.2	3.02	-3	-1.2	-0.7	0.04	-0.3	2.9	-0.7	-1.8	0.1	1	6.8	-4.7	1.2	1	0.04	-4.3	-4	-0.8	-4.6	-2.9	-6.5	1.3	-10	-8.7
0	-2	-5	-0	-15	-16	-3	-1	-0	-52	0.6	-5.6	-7	-11	7	-5.7	-34	5.5	6.22	12	4	21	14	-49	24.2	-16	20.5	-19	-7	-6	-43	-56	-57	-7	-72	23
0	-0	-2	-0	-1	-0	0.4	-1	0	0.9	-2	0.4	4.1	2.5	-0.9	3.15	2.97	-2.7	-0.2	0.8	0.2	-1	-0.5	5	-1.6	2	-3	1.75	-1	-1.8	6.7	6.7	8.9	-7	2.2	-6.9
-0	0.2	2.4	-0	-2	-2	0.7	0.4	-0	-6	-1	-1.5	1.3	1.3	3.9	0.37	-4.7	0.5	0.73	1.3	1.6	3.7	-1.3	-5	2.38	-2.7	5.88	0.16	2.5	-1.3	-2.1	-2.6	-4.3	3.2	-1.4	14
-0	0.5	1.1	-0	1	1.8	0.2	0.6	-0	0.1	4.8	0.84	-3	-2.3	3.3	-2.3	-5.2	6.6	1.06	-1	2.7	4.8	4.9	-8.9	5.24	-2.5	9.31	-2	0.2	2.19	-8.7	-8.1	-13	13	-7.8	14
-0	-0	0.3	-0	-2	-2	-1	0.4	-0	-9	2.1	-0.7	-2	-2.8	2.4	-1.8	-6.9	2.7	1.51	1.8	1.5	4.8	2.5	-10	5.48	-3.7	6.85	-2.8	-0	-0.1	-9.9	-12	-13	3	-12	9.7
0	-1	-2	0	0.8	2.3	-0	-1	0	10	-1	3.12	2.5	1.4	-5.2	5.21	11	-3.8	-0.9	-0.8	-3	-6	-0.7	13	-7.3	5.3	-11	1.73	-3	-2.1	10.1	12	16	-14	7.7	-26
-0	1.6	3.5	-0	2	2.2	1.2	1.4	-0	-2	1.6	-1.9	0.2	1.2	6.9	-4	-9.9	6.1	1.46	-1.8	5.1	6.6	2.3	-8.7	7.07	-3.6	15.4	0.92	3.7	2.41	-6.1	-2.7	-11	23	1.8	35
-0	0.6	3	-0	-3	-3	0.3	0.9	-0	-25	5.3	-0.9	-3	-3	15	-5.3	-30	14	3.66	2.4	5.8	20	14	-41	19.7	-14	34.3	-12	-1	-3.1	-33	-39	-53	25	-42	55
0	-0	-0	0	1.4	0.9	0.2	-0	0	7.2	-2	-0.1	3.7	2.9	-3.8	3.99	11.2	-6.3	-1.4	0.3	-2	-7	-6.7	16	-7.2	4.3	-11	5.13	0.8	-0.4	15.1	17	22	-11	17	-17
-0	0.7	0.4	0	3.5	2.7	0.5	0.3	-0	8.6	1.5	2.1	1.4	2	-0.2	1.01	3.45	-0.1	-0.3	-2.7	1.9	-1	0.5	5.3	-1.9	2.3	1.15	2.55	-1	0.18	7.3	8.8	7.2	6	10	1.7
-0	0.4	2.8	0	5.2	6.7	1.4	0.2	-0	16	1.9	4.05	2	4.1	1.8	2.4	7.25	2.4	-1.7	-5.1	0.3	-2	-0.6	9.4	-4.6	2.5	0.73	4.34	0.6	0.19	6.76	12	8	9.8	18	4.3
0	0.3	-1	0	3.9	4.5	-1	-1	0	8.6	-3	0.89	3.1	1.4	-4.5	-0.3	2.26	-2.3	-2.9	-3.9	-1	-4	0.2	8.3	-3	3.8	-6.8	1.34	-2	1.87	7.78	9.5	12	0.6	11	-9.2
-0	-0	0.3	0	4.6	5.9	0.7	-1	0	20	-5	1.25	3.8	5	-7.1	2.69	16	-7.7	-3.2	-4.4	-5	-12	-8.4	26	-13	8.7	-18	7.42	0.6	0.79	22.2	27	32	-8	33	-25
-0	1.8	5.4	-0	3.5	0.9	2.6	1.7	-0	10	-4	-2.7	4.4	7.2	2.8	2.11	11.3	-4.8	-0.6	-0.3	-1	-6	-13	19	-9.6	2.7	-3	9.88	10	0.64	18.1	21	20	2.2	35	11
-0	0.2	-1	-0	-10	-10	-1	1.4	-0	-45	5.5	-5.4	-10	-11	14	-13	-43	15	4.85	6	9.3	25	17	-59	29.7	-18	36	-18	-2	0.5	-50	-62	-73	25	-68	57
-0	0.9	1.3	0	6.9	6.6	0.7	0.2	0	24	-1	1.25	3.8	4.9	-6.5	3.88	21.1	-6.7	-2.5	-4	-3	-15	-11	31	-14	9	-15	11.7	3.7	2.72	25.6	34	39	-5	40	-21
-0	0.9	1.6	-0	-2	-3	-1	1.3	-0	-15	-0	-4.2	-3	-3	4.9	-6.6	-16	4.2	1.64	1.8	3.4	8.6	2.4	-18	9.81	-6.5	12.4	-4.2	2	2.15	-14	-18	-22	14	-14	28
0	-2	-5	0	2.7	6.2	1.4	-2	0	28	0.2	8.06	5	5	-9.8	11.9	29.5	-8.6	-3.6	-3.4	-4	-15	-4.2	32	-17	13	-25	7.94	-6	-3.9	28.8	34	42	-27	25	-58
0	-2	-4	-0	-4	-2	-2	-1	-0	-13	3.3	3.01	-4	-5.2	0.9	-0.6	-11	5.6	1.1	0.8	1.5	8.9	13	-20	9.12	-4.4	6.8	-11	-8	-3	-20	-23	-25	-1	-34	-2.1
0	-2	-5	0	-3	-1	-1	-2	0	-1	2	5.63	-2	-2.5	-3.3	4.38	2.18	0.7	-0.2	-0.3	-3	0.9	9.7	-5.8	-0.6	1.3	-4.6	-7.9	-9	-5.5	-6.7	-8.5	-7.9	-14	-22	-27
0	-0	-1	0	0.3	0.2	-1	-1	0	2.9	1.2	2.7	1.1	0.3	-1.1	2.77	3.35	-0.3	-0.5	-0.5	-0	-1	1.3	2	-1.8	0.8	-1	-0.2	-2	-1.7	1.3	1.4	2.6	-5	-1.7	-7.6
0	0.1	-1	-0	-4	-5	-3	0.7	-0	-32	6.3	0.49	-11	-10	10	-11	-36	16	2.02	0	6	23	20	-52	23.6	-16	29.2	-20	-8	-0.6	-47	-58	-69	26	-61	44
0	0.2	-2	-0	-9	-10	-4	1.6	-0	-51	6.2	-6.1	-13	-15	12	-15	-45	16	4.31	6	8.6	28	18	-63	33.4	-20	35.6	-20	-4	2.25	-57	-70	-78	26	-75	56
-0	1	1.7	-0	-8	-8	-2	2.6	-0	-49	5.6	-4.7	-15	-14	18	-19	-55	23	4.46	1.1	8.4	34	24	-75	35.8	-23	48	-24	-3	1.91	-70	-81	-99	46	-77	84
0	-4	-11	0	-5	-3	-3	-4	0	1.4	0.6	3.22	1.9	-3.1	-14	11.3	22	-11	-1.6	6.2	-6	-13	-0.6	19	-11	8.2	-29	-2.6	-9	-5	15.6	11	27	-52	-10	-78
0	-3	-10	-0	-16	-14	-6	-1	-0	-60	9.5	-2.8	-15	-20	6.2	-10	-45	16	6.51	11	4.8	28	29	-70	34.6	-20	27.3	-31	-14	-3.5	-68	-85	-89	-3	-110	18
0	-7	-24	0	-5	0	-2	-7	0	30	2	20.1	0.6	-1.2	-29	23.1	53.2	-20	-4.4	-1.1	-11	-26	7.2	45	-28	24	-58	-3.4	-26	-14	34.1	35	58	-85	-6.6	-158

Generation of 10-daily stream flows:

After selecting the form of model and estimating the parameters of the model, the synthetic 10-daily stream flows were generated by using the disaggregation model. The AR (1) model of the method of moment for generating the annual stream flow series was developed in the form of the equation.

$$\mathbf{Z_t = 0.3512 Z_{t-1} + 1.05290\ \varepsilon_t} \quad (17)$$

$$\mathbf{X_t = Z_t + \overline{X}} \quad (18)$$

Further, the generated annual stream flow series was obtained by using equation (17) along with a series of normally distributed random numbers. The synthetic stream flows for different 10-daily were generated by using corresponding values of A_τ, B_τ and C_τ from the matrices.

Conclusion:

The performance of disaggregation model was tested by comparing statistical characteristics, *i.e.*, mean, standard

Table 4 : Statistical characteristics of historical and generated 10-daily stream flows

Statistical characteristics		Mean (cumec)		Standard deviation (cumec)		Skewness		Kurtosis	
Months	10-daily	Historical	Generated	Historical	Generated	Historical	Generated	Historical	Generated
Jan.	1	5.71	5.92	12.30	23.13	2.5129	0.8210	9.1117	5.6230
	2	0.47	0.07	2.18	4.78	5.2034	1.1400	31.0366	3.0000
	3	0.78	0.41	3.52	39.98	5.3618	-1.8491	32.6484	7.8960
	4	4.29	5.15	12.19	64.86	3.5330	-2.0133	15.8542	8.1671
Feb.	5	2.96	3.82	7.99	50.01	2.6605	-2.2950	8.8679	9.0492
	6	4.03	9.14	8.98	23.04	2.4597	-1.0678	8.6358	4.5899
	7	1.08	1.24	3.78	64.82	4.3692	2.4018	23.6389	9.2536
Mar.	8	0.85	0.99	4.87	29.52	5.7446	-1.4794	36.0000	6.6112
	9	8.27	6.64	37.95	14.25	5.3762	0.0000	32.747	3.0000
	10	12.10	18.94	24.19	14.50	2.4787	-0.6109	9.3765	3.6336
April	11	9.81	9.88	22.22	32.58	3.6145	-2.2365	18.0529	8.0271
	12	14.40	9.59	19.57	3.69	1.7771	0.0000	5.5074	3.0000
	13	28.42	27.02	43.30	46.42	3.2720	-2.1662	14.508	7.5390
May	14	31.81	55.27	31.80	77.75	1.1078	2.2649	3.2898	8.5494
	15	46.53	39.09	50.19	32.51	2.1726	0.0414	7.3214	2.8869
	16	66.51	81.10	74.71	31.78	2.4461	2.2223	9.8166	7.5753
Jun.	17	148.14	151.90	182.83	100.15	2.8820	-1.7843	14.1514	6.3844
	18	387.79	373.00	305.00	41.53	1.1251	1.9779	4.0925	8.3643
	19	721.99	756.25	627.25	22.48	2.1665	-0.6204	9.6900	2.8463
Jul.	20	939.55	1046.22	818.73	71.96	1.6875	-2.1601	6.1709	7.0897
	21	1154.14	1137.77	739.64	49.06	0.9166	-1.2362	3.7066	4.0503
	22	1267.09	1269.24	761.14	53.70	0.6134	-1.8267	2.4733	5.9829
Aug.	23	1429.48	1528.37	868.04	46.05	0.6669	0.0000	2.8243	3.0000
	24	965.47	1079.09	592.47	94.33	0.8505	0.8244	2.7428	8.8035
	25	642.36	862.39	459.51	48.25	1.3719	-2.0514	4.9744	6.6182
Sept.	26	409.70	399.78	275.95	46.17	2.0535	-2.2068	8.6955	7.4100
	27	421.37	585.58	294.72	39.39	0.9049	-2.3899	3.2110	8.4925
	28	466.05	486.94	365.82	34.43	2.6596	-1.1694	13.2468	5.3816
Oct.	29	296.06	307.87	266.22	41.36	2.1749	2.2366	8.8993	9.1849
	30	239.82	244.40	216.31	51.61	1.6626	-2.3923	6.2621	9.0155
	31	164.01	158.26	152.77	4.09	1.7100	0.0000	6.2000	3.0000
Nov.	32	174.91	166.19	415.48	68.73	5.3861	-2.0187	33.1312	8.4771
	33	102.76	113.31	204.52	41.09	4.6255	-1.1003	26.514	3.8054
	34	52.76	66.76	53.60	52.92	1.4225	1.5979	4.4888	7.1517
Dec.	35	31.23	47.23	39.74	60.73	1.0987	-1.5240	3.0553	6.8842
	36	10.00	14.01	15.94	4.72	1.6661	3.9031	4.9384	18.5080

deviation, skewness and kurtosis of historical and generated 10-daily data. Based on the results of study the author arrived at final conclusions are the disaggregation model conserved mean, skewness and kurtosis in some cases for 10-daily stream flows (Table 4). The mean and kurtosis of generated aggregative annual stream flow is nearly equal to historical data. This property is conserved in disaggregation model.

Authors' affiliations:
A.A. ATRE, Department of Soil and Water Conservation Engineering, Dr. A.S. College of Agricultural Engineering, Mahatma Phule Krishi Vidyapeeth, Rahuri, AHMEDNAGAR (M.S.) INDIA

REFERENCES

Akaike, H. (1974). A new look at statistical model identification. *IEEE Trans. on Automatic Control, AC*, **19**(6): 716-723.

Bowen, J. and Huang, M. (1990). A comparison of maximum likelihood with method of moment procedures for separating individual and group effects. *J. Personality & Soc. Psychol.*, **58**(1) : 90-94.

Ismail, N.A., Harun, S. and Yusop, Z. (2004). Synthetic simulation of stream flow and rainfall data using disaggregation models. *J. Kejuruteraan Awam,* **16**(2): 56-65.

Lane, W.L. (1979). *Applied stochastic techniques (LAST Computer package), user manual*. Division of Planning Technical Services, Bureau of Reclamation, Denver, Colorado.

Rajakumar, K.M. and Kumar, D. (2004). Stochastic modelling of daily rainfall for southwest monsoon season of Baptala, Andhra Pradesh. *J. Agric. Engg. ISAE*, **41**(3):41-45.

Salas, J.D., Delleur, J.W., Yevjevich, V. and Lane, W.L. (1980). Applied modelling of hydrologic time series. Water Resources Publication, Michigan, USA.

7th Year
★★★★★ of Excellence ★★★★★