# SYNTHETIC GENERATION OF STREAMFLOW DATA USING COMPUTER SIMULATION MODEL 

by

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## THESIS



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## DECLARATION

I hereby declare that this thesis entitled "Synthetic Generation of Streamflow Data Using Computer"Simulation Model" is a bonafide record of research work done by me during the course of research and that the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, relationship or other similar title or any other University or Society.

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## CERTIFICATE


#### Abstract

Certified that this thesis, entitled "Synthetic Generation of Streamflow Data Using Computer Simulation Model" is a record of research work done independently by Sri. Levan, K.V. under my guidance and supervision and that it has not previously formed the basis for the award of any degree, fellowship or associateship to him.


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We, the undersigned, members of the advisory committee of Shri. Levan, K.V., a candidate for the degree of Master of Technology in Agricultural Engineering with major in Soil and Water Engineering, agree that the thesis entitled "Synthetic Generation of Streamflow Data Using Computer Simulation Model" may be submitted by Shri. Levan, K.V. in paritial fulfilment of the requirement for the degree.


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| cm | - | centimetre |
| :---: | :---: | :---: |
| dept | - | Department |
| engg | - | Engineering |
| ESO | - | Explicit Stochastic Optimisation |
| exp | - | exponential |
| Fig. | - | Figure |
| ISO | - | Implicit Stochastic Optimisation |
| Inst | - | Institute |
| Int | - | International |
| J. | - | Journal |
| km | - | kilometre |
| $\mathrm{Mm}^{3}$ | - | Million metre cube |
| 告 | - | percentage |
| Res. | - | Research |
| US | - | United States |

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## Introduction

## INTRODUCTION

Occurrence of flood is a natural phenomenon all over the world. With the increase in population and human activity in the flood plains, flood damages represent an increasing hazard in many countries, in spite of increasing investments in flood control measures. Consequently it is of utmost importance to utilise the most efficient methods in streamflow determination, in assessment of reservoir operations schemes.

Also for planning, design and operation of water resources system, it is very much essential to have streamflow data that will be at least equal to the projected useful life of reservoir. But in most of the cases, the data for the required duration is not available. In such cases, streamflow data is usually generated for required number of years. This artificially generated data known as the 'synthetic' data will have the same statistical properties as that of the available historical data of streamflows. The synthetic data can be used for the design and operation of reservoirs.

The recent years progress within hydrology and river hydraulics has now made it feasible to peform streamflow generation by means of comprehensive mathematical models. The later years rapid development in size and speed of microcomputers has now also made it feasible to develop microcomputer versions of these mathematical models.

Hydrologic simulation is an effective technique in comprehensive watershed planning and equally important in subsequent implementation and refinement. The simulation approach is essentially a search method. First a reasonable initial operation rule is postulated. Then changes in decision rule that tend to move the operation in the direction of the desired objectives are tried. This approach raspmbles the trial and error approach used in traditional operation stữies.

The practical problems of design and operation of water resources systems are steadily becoming numerous and complex. Estimations of predictions of peak flow frequencies and run-off volumes are necessary in connection with the investigation and operation of all hydroelectric as well as irrigation projects. Hydrologist have little streamflow data and limited rainfall data to use as a basis, for predicting flow behaviour at the project sites in the river basins of Western Ghats region.

The estimation of maximum expected flood in a natural drainage system has lately been given extra special attention due to unforeseen failure of civil structures. It has always been a difficult task for designer to choose the appropriate methodology while dealing with the hydrology of big structure
such as dams and spillways. The failure of large dams and allied structures attributed to the unforeseen hydrometerological events has made the hydrologist rather cautious in selecting methodology for estimating maximum expected floods. Based on the statistical information a suitable stochastic model has been attempted in the present study to correlate peak flows with their recurrence interval for the flows of a river after collecting sufficiently large number of observations. The model thus generated is expected to give reliable forecast of flows. These results have been compared with the historic data available.

Kerala with all its forty four rivers and their tributories and with copious amount of rainfall has varying streamflows in its different reaches and regions. To determine the data, the rainfall-runoff relationship for atleast one river basin and its sub-basins have to be established taking into account as far as possible the hydrometeorological, topographical, geographical and geomorphological characteristics. The type of rainfall-run off relationships and the extent of sophistication and refinement required to be employed in developing the relationships would depend not only on the data available but also on the type of water resources development contemplated in the basin.


Considering these needs, an attempt has been made to establish a computer simulation model for the synthetic generation of streamflow data for one of the larger river basins of the region, namely Chaliyar.

The Chaliyar river basin selected for the present study is the third largest in Kerala with age area of two thousand nine hundred and twel are kilometre. The river has not been so far exploitec for development of hydropower or major/mediun irrigation schemes though all these have been contemplated. The streamflow data, especially the monthly flow data, are significant for future water resources development in the basin.

For hydrologic time series modelling of monthly flows based on non-stationarity of time series, the Thomas-Fiering model is well known. This model allows for non-stationarity that is observed in monthly streamflows. It preserves the statistical parameters like mean, standard deviation and serial correlation coefficient. This model considers periodic, correlation and random components of time series of streamflows. The detailed studies revealed that a univariate first order Thomas-Fiering model would be able to adequatély represent monthly means for the Chaliyar basin.
suitable mathematical model for the synthetic data generation, based on the available streamflow data which is useful for the design and operation of water resources system.

The specific objectives are:

1. Development of a computer simulation $m$ - $}$ of synthetic data for river flows.
2. Test the model for Chaliyar river basin for statistical stability.
3. Comparison of the generated and historical data for different statistical parameters.

Review of Literature

## REVIEW OF LITERATURE

In this chapter an attempt is made to give a brief review of literature relevant to the topic of study undertaken in the past.

### 2.1 Stochastic optimisation

Many papers (Takenchi, 1972) have been published these last years in the area of stochastic optimisation. Two facts may have caused this abundance of articles. Either the problem is difficult and requires to be solved by the joint efforts of many researchers, or no general method exists and each case asks for a special treatment. In reality, the truth lies in between. Hence only the methodologies relevant for the case under study will be reviewed here. Roefs (1968) prepared a good summary of the existing procedures which Croley (1972) took over and completed.

According to Roefs, two basic methods exist to solve stochastic optimisation problems. Implicit stochastic optimisation (ISO) and explicit stochastic optimisation (ESO). Croley himself has added a third one, which is in fact a combination of ISO and ESO, the alternative stochastic optimisation (ASO) technique.

Monte Carlo Dynamic Programming introduced by Young (1967) belongs to the first category. To optimise the
operation of a reservoir under uncertainty, Young applies first a deterministic optimisation technique to each of the many available inflows sequences. The related optimal sets of releases are recorded. In a second step, the computed releases are related to some varịables like storage or inflows, that have an influence on the release strategy and that describe the state of the system. Multiple linear regression analysis is most often used in the second step. Finally the established relations supply the information required to operate the reservoir.

In the second technique, one introduces the probability distribution of the inputs directly into the optimisation procedure. Stochastic linear programming developed by Manhe.(1960) characterises well this approach. Manhe books for that set of probabilities which maximize the expected total benefit of reservoir operation. The solution of ESO consists of a table of optimal decisions indexed on the reservoir content and on the amount of previous inflow.

Finally Croley proposes a combination of both methods. First, as in ISO, the returns of the reservoir are optimized succesșively for various input samples, and then related release strategies are recorded. Second, this time in ESO, one evaluates the distribution of the decisions corresponding to the first stage of the operation period. Then an
appropriate decision, corresponding either to the mean, mode or median of the obtained statistical distribution is selected, which applied to the system brings it to the beginning of the second stage. One repeats the same procedure for the second and all, the following stages. Finally relations are established between decision and relevant state variables as in ISO. To reduce the burden of computations, the system is operated, in each case, only over a reduced period instead of the complete one.

As the ISO technique relies heavily on simulation, the problem does not have to be solvable by analytical techniques.

So input time series with long persistence can be handled without problems. The application of ISO may require a lot of computations. However the real difficulties and drawbacks of this method appear in the last step, when relations are established between decision variables and relevant parameters describing the state of the system.

### 2.2 Hydrologic simulation

Hydrologic simulation is an effective technique in comprehensive watershed planning and equally important in subsequent implementation and refinement. Waliish (1972) has studied the practical considerations involved in the use of simulation in the preparation of three comprehensive watershed
plans and has also used the results of that simulation study in implementing these plans.

Mejia et al. (1974) analysed a system that serves recreation and flow augmentation purposes. It uses flow forecasting and mathematical programming for optimisation. Historical data were used to simulate the operation of the system under different rules and an assessment of policies was made on the basis of multi-objective criteria.

Donald and Jose (1970) produced a set of simulation and optimization tools capable of analysing development and operation of a complex, multi-basin, interconnected water resource system. These models provide valuable information regarding the construction and operation of a proposed set of water projects. The simulation procedure developed by them employed a direct solution of a set of linear equations.

### 2.3 Different models in hydrology

A model is a simplified version of a complex system and a hydrological model can be either physical (Chow, 1967; Chery, 1963), analog (Diskin, 1967) or mathematical, in which behaviour of the system is represented by a set of equations, perhaps, together with logical statements expressing relationships between variables and parameters.

A continuous streamflow simulation model meant for large basin was generated in 1958 by Army Corps of Engineers (US). This model known as streamflow synthesis and reservoir regulation model (SSARR) is primarily intended for streamflow and flood forecasting and for reservoir design and operation studies. All components of run-off are routed separately and the sum of the routed values for any given time period is taken as the streamflow for the catchment.

The Boughton model (1966) originally developed in Australia was meant to simulate water yields from catchmerts in sub-humid to semi-arid regions. The model using daily rainfall and evaporation data, provides continuous simulation capability for general purpose use.

Quimpo and Yevjevich (1967) and Quimpo (1968) used a stochastic model for daily river flows. Roesner and Yevjevich (1966) studied the monthly run-off series. using, serial correlation analysis. An earlier study by Yevjevich (1964) on annual run-off sequences showed that the correlation coefficients were less than those for monthly flows. This increase in correlation with shorter time basis was also obtained by Corrigen and Huzen (1967) while analysing annual floods.

Sugawa (1967) applied TANK model for flood analysis and daily flow analysis to a number of basins in Japan and
other countries. The application to some of the basins have been described in the publication of National Research Centre for Disaster Prevention (1974). The model has found its applications in the river basins of Malaysia, Thailand, Canada and some African countries. A fèw sṭudies have been reported with regarded to river basins of India (Ekbote and Bhave, 1982).

The model structure is composed of several tanks laid vertically in series representing soil moisture and groundwater in different soil strata of the basin. The daily rainfall run-off model applicable to humid basins consists of four tanks laid vertically. The sum of outflows through side outflows of four tanks represents total run-off from the basin. Rainfall is the input to the top tank. The model is based on the hypothesis that the run-off at any instant from each tank depends on the storage in the tank at that instant and follows an exponential function. The model is non-linear in character and as much it is very difficult to find optimum parameter values using analytical techniques of optimisation. Only way of calibration is therefore, by trial and error or by using numerical techniques for optimisation.

The model is run after finalising the initial set of parameter values. The model simulates outflow hydrograph. The parameters are then calibrated leading to final model
structure. Three main characteristics that are mainly looked into for comparison are (a) peak flow value, (b) time to peak and (c) recession slopes of the hydrograph.

A single deterministic black box model for monthly rainfall-run off simulation for the monsoon season has been evolved for the Chaliyar basin on tne Malabar Coast. The monthly rainfall-run off regression relationship reveals nonlinear characteristics. The accuracy of the calibrated model has been verified using the data for the calibration period from the sub-basin. The validity of the model has been tested in another sub-basin of the chaliyar. The regionalised model can be used for assessing the streamflow from similar sub-basins, which are not gauged. The model satisfactorily preserves the monthly historical means and the standard deviations of the flows.

The present rainfall-run off model has been selected with a view to fulfil the requirements, such as (1) assessing the monthly streamflow at the ungauged sites, (ii) computing flow at sites where the measuring operation has been terminated, (iii) estimation of monthly inflows into the envisaged reservoirs, (iv) calculating missing monthly flows. The simplicity of the model makes it suitable for application by field engineers. The limitation with regard to the quality and depth of data have been the major constraints in selecting other models suitable for the purposes described.

A monthly model similar to the one applied by Minikou and Rao (1983) for the Greek catchments can be used for both linear and non-linear rainfall-run off relationships. The model was calibrated and verified only for the monsoon months. Monthly streamflow data were available for 12 years (1960-80) from the Karimpuzha and the Punnapuzha sub-basins, monthly rainfall data were also available for the same period from the stations situated in the selected sub-basins and from the adjacent sub-basins. The model was verified by comparing the flows estimated using the model with the observed flows in the Punnapuzha sub-basin of the Chaliyar. The simple monthly rainfall-run off model evolved and validated for the sub-basin will be useful for computing streamflows in the ungauged sub-basins of Chaliyar for purposes of water resources development and management. This is especially significant since there are a number of raingauges in the basin and only a few stream gauging stations.

### 2.4 Stochastic models in hydrology

Stochastic techniques have been used for synthetic generation of hydrologic data by Thomas and Fiering (1962). They generated sequences of monthly and six-hourly flood flows by a stochastic model for the monthly run-off. Monthly flows were assumed to be normally distributed the correlation coefficients between successive pairs of monthly flows were
same as those of historical records. The disaggregation problem namely that of generating a sequence of monthly streamflows which simultaneously preserves statistical properties of both the sequence of annual totals and the sequence of monthly flows has been solved by Valeneia and Schaake (1973). Singh and Lonnquist (1974) used an alternative mathod to generate monthly flows such that the annual totals retain desirable characteristics, the assumtion being monthly flows could be described by a mixture of two normal distributions. Thomas-Fiering technique was later extended by Harms and Campbell (1967) using a logarithmic transformation. Assuming normal distribution of historical flows, Brittan (1961) generated annual flows based on a Markov process. Chow and Ramaseshan (1965) used a non-stationary first order Markov chain process to describe hourly rainfall of maximum annual storms for sequential of annual floods. Using lognormally, transformed random numbers and a 'storm shifting' treatment to the rainfall data, annual storms were generated and routed through a system of linear reservoirs to arrive at the annual floods. Fiering (1964a) used a Markov model for sequential generation of daily flows which was used for lowflow analysis.

Thomas-Fiering model and autoregressive models based on the Gaussian distribution are likely to be less satisfactory than one which preserves the hydrograph characteristics of rapidly rising limb followed by more gradually
aecreasing recession. A generating model which preserves the characteristics hydrograph shape and which has been applied to the stochastic generation of daily flows, is the 'snotnoise' model. This was described by Parzen (1962) and applied to the daily streamflow generating problem by Weiss (1973).

A bivariate technique was used by Thomas and Fiering (1962) using the cross correlation of different pairs of gauging stations to generate discharges at several sites in a river basin from the recorded and generated flows at one of the stations and successive application to a chain of stations. Mstalas and Jacobs (1964) developed a procedure to generate and augment data by utilizing relationships between two given hydrologic phenomena such as rainfall and run-off.

Multivariate technique have been applied using spatial and temporal sequential correlation of hydrologic variables from stations having the same hydrologic and climatic conditions. Such a technique was first introduced by Fiering (1964b) and then developed further by Matalas (1967a, 1967b). Benson and Matalas (1967) adopted a regional analysis for hydrologic data generation for sites with short of inadequate records. Statistical techniques based on observations were combined with the knowledge of physical characteristics of the basin such as drainage area, channel slope, surface storage, precipitation and forested area, for constructing the model.

For approximating discrete fractional noise, two processes have been developed: (i) the broken-line process developed by Ditlevsen (1971) which is adapted to synthetic flow generation by Mejia (1971) and by Garcia et al. (1972) and (ii) the ARMA process (Box and Jenkins, 1970) which has been used to discuss streamflow sequences (Carlson et:al., 1970) and adapted to synthetic flow. generation. by o'connel (1974).

Auto-regressive moving average (ARMA) time series models have been extensively used of late since it has a physically reasonable correlation structure which can reflect long term persistence resulting from long memory (Mandelbrot and Wallis, 1968), although this reasoning has been argued against by Klemes (1974).- The long term persistence may also be due to shifts in the means of hydrologic processes, as demonstrated by Boes and Salas (1978). O'Connel (1971, 1974, 1977) has also pursued the long term persistence basis of the model. Multivariate ARMA ( $p, q$ ) models have been proposed by Salas et al. (1980), Loucks et al. (1981), Jenkins and Alvi (1981), Box and Jenkins (1976), Stedinger et al. (1985).

Jain et al. (1985) developed a suitable stochastic model to-give-rel-iable forecast of flows for a river. Based on the statistical information, a suitable stochastic model has been attempted to correlate peak flows with their recurrence interval for the flows of a river after collecting
sufficiently large number of observations. These results have been compared with those obtained from Gumpels method. This stochastic model establish a relation between expected peak flood and recurrence interval for a long services of recorded flows of a river scanning data from the year 1885 to 1984. The model uses Poissons Distribution applicable to investigate the encounter probability and accompanies magnitude for a remote possibility of occurrence of extreme event.

Jobi (1989) developed a computer samulation model for the operation of the multireservoir system with multiple objectives using historic and as well as generated streamflow. The objective of the study was to demonstrate the application of some of the systems analysis technique for optimal operation of water resources systems so as to later to the multi-objective needs of the population. It included the modelling for the selection of cropping pattern by conjective use of surface water and ground water, for getting maximum net, returns from the command area as well as for maximising the area of cultivation. Linear programming technique is adopted for this study.

The reservoir operation simulation model is designed for monthly operation with historic monthly mean streamflows. The monthly releases for various uses are obtained by running the model with the monthly streamflow data available for the reservoir sites from 1964 to 1983.

The linear programming model was developed by making use of the reservoir zoning concept introduced by Bend in 1967. In this study, the reservoir operation optimization model is designedfor monthly operation with generated monthly streamflows. With the generated data optimal releases from the reservoirs for various uses with the application of linear programming technique are obtained.

Twenty years of data at the three sites for the period 1964-83 has been taken in the study for the generation of streamflows. The monthly streamflow data has been checked for its consistency with normal distribution.

For hydrologic time series modelling of monthly flows wased on non-stationarity of time series, the Thomas-Fiering model is well known.

The studies conducted by Seth et al. (1985) revealed that a univariate first order Thomas-Fiering model would be able to adequately represent monthly means for the Chaliyar basin.

Ranga and Narasimhamurthy (1990) reported the generation of synthetic data of Cavery river flows. ThomasFiering model has been fitted to the observed monthly streamflows and after verification, data has been generated for a period of four hundred and ten years. For the study, data has
been obtained from Chunchanakatto gauge station which is almost forty eight kms, upstream of Krishnaraja Sagara Dam. Data is available from Nineteen hundred and sixteen. The statistical parameters are found from the historical data. Trend component has not been consdered in this model because, it was observed from Kendal and Stuart's turning point test that there is no trend in the thirty years (1916 to 1945) data considered .

For the model verification, the total length of fifty years of data (1916 to 1965) was divided into two parts. First part having data of thirty years that was used to form the regression equations and then data was generated for twenty years, second part consists of twenty years of data that was used for comparing with the generated twenty years of data. The validation procedure includes (a) comparison of statistical prameters of historical and generated data (b) comparison of flow duration curves based on the generated data with the curves based on the historical data. Form the model verification tests, it was found that the Thomas-Fiering Model holds good for the site selected. Hence data was generated for a period of four hundred and ten years. First ten years of generated data was ignored to account for error caused due to initialisation of the generating sequence.

Materials and Methods

The objective in general of this research work is to develop a suitable mathematical model for the synthetic data generation, based on the available streamflow data which is useful for the design and operation of water resources systems.
3.1 Objective

The specific objectives of this study are:

1. Development of a computer simulation model for generation of synthetic data for river flows.
2. Test the model for Chaliyar river basin for statistical stability.
3. Comparison of the generated and historical data for đifferent statistical parameters.

### 3.2 Theoretical background

Few hydrologic populations can be represented by the normal distribution, and the degree of skewness depends upon the type of data. For example the distribution of daily flows is much more skewed than the distribution of annual flows. Since many of the statistical methods and techniques are
primarily based the normal distribution, it has often been found advantageous to transform a skewed distribution into the normal one. Theoretically it is always possible to determine a function that would yield such a transformation (Hold, 1962), eventhough some transformations may be quite involved.

One of the most important and useful of such informations is the logarithmic transformation. It has been observed for the data having considerable skewness, their logarithms, are nearly normally distributed, and hence the original data are said to follow the log normal distribution.


#### Abstract

Many hydrologic time series exhibit significant correlation. That is the value of the random variable under consideration at one time period is correlated with the values of the random variable at earlier time periods. The correlation of a random variable $X$ at one time period with its value $k$ time periods earlier is denoted by $P_{k}(k)$ and is called the $k$ th order serial correlation. If $P_{x}(k)$ can be approximately by $P_{x}(k)=P_{x}^{k}(1)$, then the time series of the random variable $X$ might be modelled by a first order Markov Process. A first order Markov process might also be used for a model if serial correlations for lags greater than one are not important.


A first order Markov process is defined by the equation

$$
\begin{align*}
x_{i}+1 & \left.=\mu_{x}+p_{x}(1)\left(x_{i}-\mu_{x}\right)+\mathbf{e}_{i+1}\right)  \tag{1}\\
\sigma_{e}^{2} & =\sigma_{x}^{2}\left[1-p_{x}^{2}(1)\right] \tag{2}
\end{align*}
$$

If the distribution of $x$ is $N\left(\mu_{x}, \sigma_{x}^{2}\right)$ then the distribution of, is $N\left(0, \sigma_{\epsilon}^{2}\right)$. If $t$ is $N(0,1)$, then $t \sigma_{\epsilon}$ or $x$ $t \sigma_{x} \sqrt{1-P_{x}^{2}(1)}$ is $N\left(0, \sigma_{E}^{2}\right)$. Thus a model for generating X 's that are $N\left(\mu_{x}, \sigma_{x}^{2}\right)$ and follow the list order Markov model is

$$
\begin{equation*}
x_{i+1}=\mu_{x}+p_{x}(1)\left(x_{i}-\mu_{x}\right)+t_{i+1} \sigma_{x} \sqrt{1-p_{x}^{2}(1)} \tag{3}
\end{equation*}
$$

3.3 Thomas-Fiering model

Thomas and Fiering (Tl, 1962) have developed a recursive equation to model the monthly flows. This follows a lag-one Markov generation scheme, given by:

$$
\begin{equation*}
x_{i+1}=x_{j+1}+b_{j}\left(x_{i}-x_{j}\right)+t_{i} \sigma_{j+1}\left(1-r_{j}^{2}\right)^{\frac{1}{2}} \tag{4}
\end{equation*}
$$

where,
$x_{i} \quad$ - discharge during the $i^{\text {th }}$ month
$x_{i+1}$ - discharge during the (i+1)st month
$x_{j}, x_{j+1}-$ mean monthly discharge during $j^{\text {th }}$ and (j+l)st month respectively, within a repetitive annual cycle of 12 months.
$b_{j} \quad-\quad$ the regression coefficient for estimating flow in the ( $j+1$ )st from the $j^{\text {th }}$ month
$t_{i} \quad-\quad$ a random normal variate with $N(0,1)$
$\sigma_{j+i}$ - is the standard deviation of flows in the (j+1 )st month
$r_{j}$ - the correlation coefficient between the flows of the $j^{\text {th }}$ and ( $j+1$ )th month

The flow chart of this model is given in Fig. 2 .
3.4 Two parameter model

The generation of sequence of monthly flows given by two-parameter Thomas-Fiering scheme is

$$
\begin{equation*}
Y_{i}=\mu_{r}+b_{r}\left(x_{i-1}-\mu_{r}\right)+\sigma_{r}\left(1-P_{r}^{2}\right)^{\frac{1}{2}} \epsilon_{i} \tag{5}
\end{equation*}
$$

where, $\mathcal{\mu}_{r^{\prime}} \sigma_{r}$, and $P_{r}$ are the mean, standard deviation and lag 1 correlation coefficient of the transformed $y$ distribution and $\epsilon_{i}$ is a random variate from $N(0, i)$. For example, if the monthly flows follow a log-normal distribution, then, ' $\mu_{r}, \sigma_{r}$ and $P_{r}$ are obtained for the sequence of natural logarithms of the observed flows $\left(X=\log _{e} X\right)$ and $i$ is drawn from a normal distribution having mean zero and unit variance. The transformed parameters are used. in eg. 5 to obtain a generated sequence. This sequence is to be inverse transformed ( $\mathrm{X}=\operatorname{antilog} \mathrm{Y}$ ) to obtain the generated flows. By this, the statistics of the historical flows may not be
preserved well in the generated flows. To overcome this difficulty, Matalas (M1) suggested certain relationships between the statistics calculated from the historical data ( $\left.\mu_{x}, \sigma_{x}, P_{x}\right)$, and the statistics of the transformed sequence $\left(\mu_{s}, \sigma_{r}, P_{r}\right)$, which are given by

$$
\left.\left.\begin{array}{rl}
\mu_{x} & =\exp \left[0.5 \sigma_{r}^{2}+\mu_{r}\right] \\
\sigma_{x}^{2} & =\exp \left[2\left(\sigma_{r}^{2}+\mu_{r}\right)\right]-\exp \left[\sigma_{r}^{2}+2\right.
\end{array} \mu_{r}\right] \quad \begin{array}{l}
2 \\
\rho_{x} \tag{8}
\end{array}=\left[\exp \left(\sigma_{r}^{2} P_{r}\right)-1\right] /\left[\exp \left(\sigma_{r}^{2}\right)-1\right]\right] .
$$

The generation scheme used in this study for the case of lognormal two parameter distribution is given in Fig. 3

### 3.5 Three parameter model

If the resemblance between the synthetic flows and historical flows is to be extended to the skewness also, it is preferable to go for the 3-parameter distribution of either lognormal or gamma. In case of gamma variates, the transformation of the same to normal variates could be done by the Wilson-Hilferty transformation if $|\gamma|<3$ and by a modified transformation if $Y<3$. However, this study is limited to using only the 3 -parameter lognormal distribution and not the gamma distribution.

If the observed sequence ( $X$ ) is assumed to follow the three-parameter, log normal distribution,

$$
\begin{align*}
\mathrm{Y} & =\log (x-a)  \tag{9}\\
\mu_{x} & =a+\exp \left[\left(\sigma_{r}^{2} / 2\right)+\mathcal{L}_{r}\right] \tag{10}
\end{align*}
$$

in which the third parameter, 'a', provides the extra degree of freedom needed to fit the lognormal model to the first three moments of the historical record. The observed sequence is shifted by the amount $a$, and the resulting sequence is then treated by the two-parameter log normal algorithm for generating a synthetic sequence.

Further, an additional equation is added, which in reproduce the coefficient of skewness of the observed sequence, $Y_{X}$.

$$
\begin{equation*}
Y_{x}=\frac{\left[\exp \left(3 \sigma_{r}^{2}\right)-3 \exp \left(\sigma_{r}^{2}\right)+2\right]}{\left.\left[\exp \left(\sigma_{r}^{2}\right)-\right]\right]} \tag{11}
\end{equation*}
$$

The procedure for generating synthetic events that will resemble the historic events in terms of $\mu_{x}, \sigma_{x}, \gamma_{x}$ and $r_{x}(1)$ is as follows. The values of $\mu_{x}, \sigma_{x}, \gamma_{x}$ and $r_{x}$ are set equal to the right handside of equation $6,7,8$ and 12 where upon the solutions of these equations give the values of a, $\mu_{r}, \sigma_{r}$, and $r_{r}(1)$.

A direct solution is proposed by Randal (RI) to solve the system of equations $6,7,8$ and 11 by making the substitution

$$
\begin{equation*}
\phi=\exp \left(\sigma_{r}^{2}\right) \tag{12}
\end{equation*}
$$

Equation 11 becomes

$$
\begin{equation*}
Y_{\mathrm{x}}=\frac{\phi^{3}-30+2}{(\phi-1)^{3 / 2}}=(\varnothing-1)^{1 / 2}(\phi+2) \tag{13}
\end{equation*}
$$

where $\varnothing \neq 1$.

From the equation 13 , it is seen that $\varnothing$ is always greater than or equal to $l$, and the right-hand side is always greater than zero. The last equation also shows that the 3 -parameter log-normal transformation is applicable to distributions with positive coefficient of skewness. So for $Y_{x}>0$. eg. 13 has one real root only.

After finding out the value of $\varphi$ from a given value of $x$, then the three parameters $\sigma_{r}, \mu_{r}$ and a can be computed from equations ll, 7 and 10.

With the values for. a, $\mu, \quad Y, Y(1), \quad$ eg. 5 may be used to generate a sequence of ${ }^{r} y^{\prime}$ s. ${ }^{r}$ Finally to the antilog of each value of $y$, the value of a is added to obtain the synthetic sequence of flows that will resemble the


It is observed that while the results using the 2-parameter log-normal distribution do not produce negative flows the 3-parameter distribution may produce negative flows if 'a' is negative (R2). In such a case, after generation, the negative flows are to be set to zero and then the properties are computed. The generation scheme used in this study for the case of log normal three parameter distribution is given in Fig. 4 .

### 3.6 Generation of monthly streamflows

Data generation procedure is used to provide equally likely flow sequences to historical one in capacity yield analysis. The Thomas Fiering model is a well known model for hydrologic time series modelling of monthly flows based on nonstationarity of time series. From the previous studies conducted for Chaliyar basin, it is seen that a univariate first order Thomas Fiering model would be able to adequately represent monthly means for this basin (Seth et al., 1985).


CALL EXAM, WHICH USES SUBROUTINE BASIC TO PRODUCE MONTHLY MEANS, S.D.'S, AND THE SLOPE AND CORRELATION COEFFICIENT FROM THE REGRESSION OF EACH MONTH ON THE PRECEDING MONT'H.

USEING ABOVE INFORMATION, ESTIMATE
THIS MONTHS FLOWLY REGRESSION OF
LAST MONTHS FLOW.:
RESIDUAL $=$ OBSERVED FLOW - ESTIMATED FLOW


INCORPORATE THESE ERRORS IN THE REGRESSION EQUATIONS TO OBTAIN SIMULATED FLOW

CALL EXAM FOR DETAILS OF SIMULATION,TO COMPARE WITH THE ACTUAL DATA


Fig. 2 FLOW CHART OF THOMAS FIERING MODEL



FIG. 3 LOGIC OF 2 PARAMETER MONTHLY MODEL



FIG. 4 LOGIC OF THOMAS FIERING MONTHLY MODEL: 3 PARAMETER LOG NORMAL DISTRIBUTION

The program listing for the Thomas-Fiering model is given in Appendix. To use the model to generate monthly flows at a site, thirty six parameters, i.e., monthly means, standard deviation and lag one serial correlations are required. These are obtained from the analysis of monthly historical flows. The statistical characteristics of monthly flows are computed for all the three sites. Though in some months, the monthly flows are non-normal, in general normality assumption could be reasonable as far as application of Thomas-Fiering model is concerned.

Monthly streamflows for the three locations and their statistical parameters are given in Tables 1,2\&3. The mean, standard deviation and correlation with previous months have been calculated using the following equations.

$$
\begin{aligned}
& \sum_{i=1}^{N} X_{i, j} \\
& X_{j}=\underline{i=1}{ }^{i, j} \\
& S_{j}=\sum_{i=1}^{\mathbb{M}} \frac{x_{i, j}-x_{j} j^{2}}{N-1} \\
& \text { N } \\
& V_{j}=\operatorname{i=1}_{j+1}\left(X_{i}-\bar{X}_{j}\right) \\
& \left.\sum_{i=1}^{N}\left(x_{i, j}-x_{j}\right)^{2}\right]^{0.5}\left[\sum_{i=1}^{n}\left(x_{i+1}-x_{j+1}\right)^{2}\right] \quad 0.5
\end{aligned}
$$

The computation for generation of data has been performed in Siemens 7580 E Computer System of I.I.T., Madras.

### 3.7 Model verification

Before a data generation model is used in generation of data, it is necessary to check that it satisfactorily reproduces the main statistical characteristics defining the streamflow process. For this purpose, the historic data is used. to form the regression equations and then data was generated for required number of years.

Twenty years of data at the three locations for the period 1964-83 has been taken in the present study for the generation of streamflows. Various graphs showing the mean monthly inflows, correlation of inflows to the previous months flow and standard deviation of historic and generated flows were drawn. The comparison of historic and generated data is effected from these plots.

### 3.8 Statistical analysis

The consistency of the monthly streamflow data has been checked with normal distribution. For all the three locations, the normal distribution test were performed and the agreement of historic and generated data was checked.

The frequency analysis of the monthiy streamflow data at all the tree sites has been done by Weibuli's method. Probability $P=m / N+1$ where $m$ is the rank of streamflow values arranged in descending order, $N$ is the length of the inflow record and return period $T=1 / P$. Using these values probability curves have been drawn for all the twelve months.

The statistical analysis of annual flows has been performed by comparing the mean, standard deviation and coefficient of correlation of both historic and generated data.

Results and Discussion

## RESULTS AND DISCUSSION

The results of the simulation model verification and the statistical analysis of the generated data are discussed in this Chapter.

### 4.1 Model verification

Twenty years of data at the three locations for the period $1964-83$ has been collected from the river gauge stations for the generation of streamflow. The data is presented in Tables 1, 2 and 3.

Figure 5 shows the mean monthly inflows to the three locations. Fig. $6,7 \& 8$ gives the correlation of inflows to the previous months flows at all three locations. The standard deviations of historic and generated flows were compased and they are shown in figures $22,23 \& 24$. There is a good agreement between the standard deviation curves of both historic and generated data for almost all the months.

The data is generated for hundred years using the Thomas Fiering Model for the three locations. This generated data is presented in Tables $5,6 \& 7$.

Table 1. Monthly streamflows at location one in Mm $^{3}$ from 1964-1983

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 6.1 | 4.5 | 5.2 | 4.0 | 5.9 | 10.9 | 41.8 | 68.2 | 15.4 | 12.5 | 13.3 | 7.2 |
| 0.9 | 0.1 | 2.2 | 1.6 | 1.5 | 8.1 | 36.7 | 33.8 | 20.6 | 13.8 | 8.7 | 7.9 |
| 2.3 | 1.8 | 1.7 | 1.0 | 1.9 | 4.3 | 20.6 | 15.9 | 17.0 | 23.4 | 9.5 | 5.5 |
| 3.5 | 1.5 | 1.9 | 2.0 | 8.7 | 19.2 | 16.1 | 14.3 | 4.1 | 7.0 | 1.7 | 6.1 |
| 3.4 | 3.3 | 4.3 | 3.9 | 4.0 | 9.1 | 37.3 | 42.5 | 20.8 | 11.6 | 9.0 | 7.0 |
| 4.0 | 2.9 | 2.2 | 2.4 | 2.9 | 7.3 | 54.9 | 40.9 | 25.1 | 44.0 | 31.0 | 22.1 |
| 20.2 | 13.4 | 7.3 | 13.4 | 27.0 | 31.2 | 79.5 | 101.4 | 59.5 | 53.5 | 18.9 | 10.1 |
| 8.9 | 7.1 | 7.0 | 6.7 | 8.3 | 23.5 | 25.4 | 24.3 | 19.1 | 36.4 | 24.9 | 23.6 |
| 18.9 | 15.4 | 14.0 | 0.7 | 2.8 | 4.2 | 15.8 | 11.0 | 3.9 | 10.9 | 4.9 | 2.7 |
| 1.8 | 1.1 | 1.0 | 1.0 | 1.2 | 19.2 | 49.6 | 55.6 | 21.5 | 8.5 | 5.4 | 3.9 |
| 1.2 | 0.3 | 0.1 | 0.2 | 1.9 | 1.8 | 45.4 | 66.4 | 37.4 | 26.5 | 12.3 | 13.4 |
| 12.9 | 10.8 | 10.0 | 7.3 | 11.5 | 35.8 | 47.8 | 34.8 | 43.6 | 36.0 | 24.4 | 13.9 |
| 8.4 | 6.0 | 2.9 | 4.7 | 1.9 | 4.4 | 23.9 | 50.9 | 38.5 | 14.4 | 18.3 | 9.8 |

Table 1 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug. | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 8.2 | 8.8 | 9.1 | 6.8 | 10.6 | 15.8 | 53.5 | 43.3 | 33.7 | 34.7 | 25.2 | 11.6 |
| 12.1 | 8.3 | 6.0 | 4.8 | 8.0 | 22.4 | 66.2 | 103.6 | 44.0 | 23.9 | 74.4 | 16.1 |
| 8.9 | 5.1 | 4.0 | 2.7 | 3.4 | 21.1 | 60.8 | 130.6 | 25.9 | 21.7 | 22.0 | 10.0 |
| 2.5 | 1.4 | 0.7 | 1.1 | 2.8 | 50.0 | 108.6 | 60.8 | 33.5 | 35.0 | 27.4 | 5.7 |
| 1.3 | 0.4 | 0.8 | 0.4 | 1.5 | 20.1 | 28.0 | 80.7 | 32.8 | 18.3 | 7.8 | 4.3 |
| 5.5 | 3.1 | 1.2 | 1.0 | 5.3 | 11.9 | 23.8 | 48.9 | 20.0 | 13.0 | 24.0 | 6.7 |
| 2.6 | 1.7 | 0.8 | 0.3 | 1.3 | 6.4 | 27.4 | 49.3 | 65.3 | 35.0 | 19.6 | 1.7 |

## Means

8.1
5.8
4.6
3.6
6.3
19.1
46.8
66.6
34.2. 26.3
22.1
10.3

Standard deviations
$\begin{array}{ll}6.3 & 4.9\end{array}$
3.8
6.9
13.5
25.9
32.8
16.2
12.7
16.8
5.8

Slopes
$-0.02$
1.5
0.6
0.2
0.5
0.3
0.20 .1
0.7
0.8
0.6
0.9

Correlations with previous month
$-0.01$
0.5
0.4
0.6
0.2
0.5
0.1
0.9
0.9
0.5
0.9

Table 2. Monthly streamflows at location two in $\mathrm{Mm}^{3}$ from 1964 to 1983

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 2.5 | 1.0 | 0.8 | 0.7 | 1.1 | 33.6 | 145.9 | 274.7 | 66.2 | 53.0 | 36.2 | 4.4 |
| 2.9 | 0.6 | 0.0 | 1.6 | 5.8 | 56.9 | 177.8 | 73.9 | 40.8 | 37.9 | 24.8 | 0.1 |
| 7.7 | 5.5 | 4.2 | 4.5 | 11.4 | 40.4 | 126.6 | 64.8 | 53.6 | 90.6 | 36.7 | 20.6 |
| 6.8 | 2.2 | 0.4 | 1.2 | 10.6 | 66.0 | 244.0 | 125.3 | 29.8 | 30.7 | 21.7 | 8.2 |
| 4.2 | 2.2 | 3.9 | 5.7 | 13.0 | 41.0 | 175.0 | 100.6 | 42.2 | 45.0 | 21.0 | 6.7 |
| 3.2 | 2.7 | 2.7 | 19.3 | 20.0 | 2.3 | 214.6 | 77.0 | 51.2 | 57.4 | 351.2 | 28.6 |
| 6.3 | 1.8 | 0.5 | 3.1 | 28.7 | 59.5 | 234.2 | 257.3 | 94.5 | 102.7 | 40.4 | 7.7 |
| 23.0 | 17.1 | 15.8 | 14.3 | 49.4 | 274.7 | 218.9 | 179.1 | 106.6 | 132.4 | 56.2 | 39.0 |
| 21.6 | 17.8 | 17.1 | 16.7 | 30.3 | 39.3 | 142.8 | 61.3 | 40.6 | 56.8 | 35.6 | 30.2 |
| 32.1 | 23.4 | 22.3 | 21.8 | 22.6 | 108.6 | 182.4 | 144.6 | 61.8 | 58.5 | 48.8 | 36.9 |
| 13.4 | 7.5 | 6.4 | 14.8 | 24.8 | 28.9 | 482.1 | 408.4 | 148.7 | 106.0 | 33.9 | 20.1 |
| 16.8 | 14.1 | 15.4 | 11.8 | 19.0 | 194.9 | 144.7 | 322.6 | 133.8 | 102.1 | 81.3 | 19.7 |
| 13.7 | 10.4 | 9.1 | 9.5 | 9.6 | 15.7 | 145.4 | 174.2 | 90.4 | 36.0 | 53.6 | 20.3 |

Contd.

```
Table 2. (Contd.)
```

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 3.8 | 1.3 | 1.1 | 1.1 | 14.2 | 122.2 | 262.8 | 97.2 | 99.9 | 91.9 | 67.0 | 18.6 |
| 8.0 | 2.7 | 2.0 | 2.1 | 6.7 | 121.4 | 253.7 | 255.9 | 62.4 | 36.4 | 124.0 | 14.7 |
| 6.9 | 2.6 | 1.9 | 1.0 | 6.3 | 66.5 | 191.0 | 336.1 | 40.1 | 27.5 | 27.8 | 12.3 |
| 5.0 | 3.4 | 1.6 | 2.3 | 6.4 | 217.5 | 381.5 | 132.0 | 50.1 | 54.6 | 26.4 | 13.1 |
| 8.8 | 4.4 | 2.5 | 2.7 | 5.8 | 229.7 | 247.4 | 416.9 | 191.2 | 86.8 | 42.3 | 16.8 |
| 2.9 | 1.4 | 0.0 | 0.0 | 2.6 | 62.2 | 233.1 | 221.8 | 19.1 | 12.0 | 15.8 | 2.9 |
| 5.3 | 2.1 | 1.9 | 1.5 | 1.7 | 130.9 | 244.1 | 247.7 | 145.3 | 61.4 | 34.8 | 17.1 |

## Means

$\begin{array}{lllllllllllllllllll}11.89 & 7.90 & 7.35 & 9.07 & 19.06 & 84.37 & 215.65 & 186.03 & 75.39 & 69.58 & 71.37 & 20.28\end{array}$
Standard deviations

| 3.36 | 7.36 | 7.32 | 7.32 | 11.71 | 75.18 | 88.67 | 112.15 | 37.20 | 33.87 | 85.03 | 10.31 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | slopes


| 0.35 | 0.84 | 0.99 | 0.76 | 0.88 | 3.20 | -0.08 | 0.68 | 0.20 | 0.67 | -0.18 | 0.03 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

Correlation with previous month
0.41
0.98
0.99
0.76
$0.55 \quad 0.50 \quad-0.07$
0.54
0.60
$0.74-0.07$
0.27
?able 3. Monthly streamflows at location three in $\mathrm{Mm}^{3}$ from 1964 to 1983

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 24.9 | 12.8 | 9.6 | 3.1 | 26.5 | 99.9 | 688.6 | 368.6 | 327.7 | 534.6 | 211.2 | 73.3 |
| 46.9 | 18.2 | 7.4 | 5.4 | 38.2 | 285.4 | 1373.4 | 927.5 | 230.2 | 207.4 | 123.4 | 817.9 |
| 51.2 | 26.5 | 20.7 | 27.3 | 46.9 | 313.6 | 1770.8 | 1018.7 | 423.3 | 267.8 | 183.3 | 92.9 |
| 50.3 | 29.8 | 17.6 | 20.5 | 44.3 | 327.5 | 274.9 | 970.4 | 548.5 | 376.2 | 213.7 | 152.0 |
| 77.9 | 52.6 | 43.2 | 52.9 | 141.6 | 80.7 | 1559.1 | 1667.5 | 464.4 | 585.5 | 218.9 | 101.8 |
| 41.7 | 24.6 | 18.3 | 19.5 | 83.4 | 1069.2 | 813.1 | 636.8 | 386.1 | 427.9 | 148.5 | 91.5 |
| 44.2 | 27.3 | 17.3 | 15.4 | 85.5 | 163.4 | 969.0 | 404.9 | 164.9 | 304.5 | 171.4 | 107.3 |
| 46.5 | 22.2 | 14.4 | 13.0 | 19.6 | 447.4 | 887.9 | 711.2 | 230.7 | 155.7 | 122.8 | 61.1 |
| 33.0 | 16.5 | 9.2 | 13.9 | 28.8 | 83.0 | 1251.3 | 1130.5 | 537.9 | 367.0 | 109.9 | 59.9 |
| 25.2 | 18.0 | 19.3 | 13.9 | 21.0 | 757.8 | 646.0 | 1157.5 | 541.5 | 401.1 | 309.5 | 54.8 |
| 51.6 | 31.5 | 21.6 | 28.6 | 15.4 | 40.8 | 609.8 | 743.8 | 507.4 | 162.7 | 234.2 | 83.0 |
| 43.1 | 25.5 | 19.0 | 19.5 | 72.5 | 562.2 | 1131.8 | 565.1 | 525.3 | 546.9 | 346.6 | 141.7 |
| 33.4 | 11.5 | 5.9 | 4.2 | 11.5 | 572.5 | 1147.6 | 1316.1 | 368.6 | 149.1 | 465.5 | 62.1 |

Table 3 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 33.4 | 13.3 | 6.8 | 5.5 | 35.7 | 363.5 | 1052.3 | 1526.9 | 243.1 | 150.5 | 170.8 | 63.5 |
| 75.9 | 44.0 | 32.3 | 39.7 | 69.5 | 487.0 | 584.1 | 962.9 | 502.7 | 648.9 | 279.6 | 89.8 |
| 28.4 | 17.4 | 10.2 | 6.7 | 24.8 | 60.8 | 196.4 | 604.3 | 216.1 | 171.5 | 315.8 | 118.1 |
| 52.3 | 30.7 | 23.6 | 28.6 | 26.0 | 153.2 | 1062.6 | 934.0 | 461.9 | 498.9 | 227.8 | 273.7 |
| 31.3 | 21.5 | 16.2 | 16.4 | 49.5 | 94.0 | 1498.0 | 1415.8 | 457.7 | 222.3 | 271.5 | 27.8 |
| 38.6 | 20.4 | 13.0 | 15.8 | 17.0 | 189.5 | 704.7 | 678.1 | 210.6 | 266.9 | 219.5 | 196.4 |
| 26.2 | 14.5 | 11.7 | 7.2 | 29.1 | 212.4 | 732.5 | 863.8 | 351.3 | 206.1 | 315.8 | 36.7 | Means

$\begin{array}{lllllllllllll}43.1 & 23.6 & 16.5 & 17.3 & 47.9 & 366.5 & 1012.5 & 938.9 & 392.8 & 331.2 & 216.5 & 140.1\end{array}$ standard deviations

| 13.5 | 10.6 | 9.5 | 13.0 | 36.2 | .292 .6 | 401.7 | 396.4 | 134.8 | 155.7 | 98.9 | 197.4 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | Slopes

0.02
0.72
0.85
1.32
1.96
$-0.13$
$-0.256$
0.382
0.074
0.510
$0.046-0.52$

Correlation with previous month
0.23
0.92
0.95
0.96
$\begin{array}{llll}0.71 & -0.02 & -0.187 & 0.387\end{array}$
0.217
0.441
$0.073-0.26$

Table 4 Normal distribution test for inflows at location two


Table 5 Generated flows of location one for 100 years (No transformation)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 10.059 | 6.437 | 6.112 | 6.451 | 14.876 | 31.279 |
| 2.221 | 0.000 | 0.000 | 0.000 | 0.000 | 19.744 |
| 3.035 | 2.188 | 2.081 | 3.862 | 8.890 | 20.736 |
| 0.000 | 1.233 | 0.763 | 0.000 | 0.000 | 0.000 |
| 13.483 | 10.083 | 12.623 | 10.888 | 16.083 | 32.419 |
| 4.309 | 2.082 | 0.801 | 3.013 | 5.260 | 30.255 |
| 12.101 | 8.939 | 6.402 | 3.171 | 5.972 | 14.171 |
| 5.201 | 4.292 | 1.787 | 2.640 | 3.729 | 15.523 |
| 1.377 | 0.975 | 0.000 | 0.000 | 0.000 | 0.000 |
| 12.371 | 9.491 | 7.650 | 7.350 | 15.218 | 7.898 |
| 10.795 | 9.160 | 5.740 | 1.220 | 0.000 | 27.542 |
| 9.218 | 6.548 | 1.365 | 3.704 | 5.265 | 11.966 |
| 3.924 | 3.770 | 4.450 | 4.068 | 4.359 | 23.109 |
| 10.147 | 7.568 | 4.745 | 2.124 | 1.729 | 1.793 |
| 6.212 | 2.633 | 1.951 | 2.892 | 3.658 | 23.888 |
| 7.722 | 7.586 | 5.434 | 5.310 | 6.931 | 15.809 |
| 9.077 | 7.619 | 7.350 | 6.316 | 18.431 | 25.133 |
| 8.413 | 5.256 | 2.289 | 1.724 | 2.403 | 0.000 |
| 5.834 | 3.708 | 2.554 | 0.000 | 0.000 | 12.412 |
| 4.468 | 3.599 | 1.786 | 0.144 | 0.432 | 2.257 |
| 10.870 | 8.382 | 5.956 | 0.000 | 0.000 | 7.846 |
| 11.288 | 7.114 | 8.723 | 5.768 | 7.435 | 20.558 |


| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 66.838 | 129.289 | 43.470 | 29.000 | 25.132 | 9.795 |
| 53.326 | 30.581 | 37.666 | 25.356 | 9.206 | 7.204 |
| 68.849 . | 85.926 | 40.422 | 34.071 | 30.244 | 5.208 |
| 8.109 | 59.083 | 10.751 | 7200 | 28.559 | 19.228 |
| 38.760 | 28.635 | 58.201 | 28.843 | 18.497 | 5.772 |
| 91.477 | 101.425 | 21.548 | 20.365 | 32.468 | 15.119 |
| 50.432 | 70.236 | 43.094 | 17.478 | 26.403 | 7.551 |
| 56.310 | 84.570 | 47.514 | 21.023 | 0.986 | 5.093 |
| 20.681 | 19.423 | 20.435 | 16.547 | 38.687 | 14.689 |
| 38.408 | 50.138 | 24.349 | 22.598 | 38.912 | 15.742 |
| 34.092 | 19.926 | 14.247 | 22.027 | 16.893 | 12.458 |
| 1.380 | 61.591 | 19.325 | 9.368 | 52.732 | 9.239 |
| 38.170 | 32.737 | 45.447 | 38.178 | 26.144 | 12.220 |
| 33.421 . | 46.694 | 0.000 | 19.636 | 15.136 | 13.051 |
| 10.616 | 16.363 | 22.182 | 28.892 | 56.973 | 14.622 |
| 44.213 | 78.862 | 24.341 | 19.100 | 10.297 | 11.968 |
| 43.211 | 17.135 | 0.481 | 7.247 | 35.455 | 11.693 |
| 13.320 | 53.698 | 17.743 | 29.283 | 17.942 | 11.445 |
| 49.236 | 46.904 | 27.850 | 21.556 | 31.466 | 6.388 |
| 9.849 | 38.681 | 16.510 | 20.010 | 24.023 | 13.531 |
| 57.188 | 51.810 | 51.439 | 36.659 | 50.236 | 16.469 |
| 40.417 | 53.178 | 6.918 | 1.896 | 0.000 | 0.985 |

Contd.

```
Table 5 (Contd.)
```

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 7.609 |
| 6.298 | 5.391 | 5.058 | 1.891 | 4.195 | 4.055 |
| 4.851 | 5.125 | 2.978 | 2.920 | 3.392 | 3.972 |
| 0.000 | 0.000 | 0.000 | 2.418 | 3.684 | 0.977 |
| 4.112 | 3.703 | 4.268 | 2.344 | 1.485 | 17.977 |
| 14.995 | 10.696 | 8.471 | 5.793 | 8.954 | 28.473 |
| 1.322 | 2.132 | 2.357 | 0.058 | 2.587 | 10.888 |
| 11.386 | 10.154 | 8.068 | 7.566 | 8.048 | 23.944 |
| 0.000 | 0.912 | 3.877 | 0.942 | 1.658 | 6.109 |
| 14.686 | 11.845 | 8.101 | 2.856 | 0.000 | 10.496 |
| 3.521 | 2.335 | 2.753 | 8.260 | 15.170 | 38.617 |
| 17.078 | 13.639 | 9.639 | 0.000 | 0.000 | 5.050 |
| 16.169 | 11.636 | 7.880 | 5.436 | 7.377 | 0.000 |
| 9.305 | 6.187 | 5.332 | 3.318 | 3.714 | 27.197 |
| 7.876 | 5.477 | 5.994 | 4.507 | - 4.928 | 9.973 |
| 14.413 | 12.095 | 11.202 | 4.512 | 7.648 | 21.196 |
| 3.646 | 1.341 | 1.391 | 3.464 | 3.701 | 24.135 |
| 7.309 | 5.766 | 4.479 | 4.85? | 8.927 | 25.127 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 13.051 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 11.360 |
| 0.000 | 0.767 | 1.816 | 4.438 | 7.199 | 10.224 |
| 2. 637 | 1.271 | 3.170 | 2.564 | 12.898 | 29.880 |

Table 5 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 44.221 | 67.142 | 54.448 | 36.662 | 48.175 | 7.380 |
| 15.635 | 16.912 | 20.714 | 29.750 | 22.072 | 10.530 |
| 15.360 | 72.442 | 48.362 | 30.731 | 21.098 | 0.000 |
| 23.833 | 63.632 | 44.406 | 34.740 | 20.256 | 2.548 |
| 80.409 | 50.711 | 17.477 | 23.454 | 19.983 | 15.738 |
| 45.459 | 38.147 | 35.147 | 21.865 | 27.832 | 5.156 |
| 70.411 | 104.897 | 31.816 | 15.496 | 8.400 | 13.239 |
| 86.449 | 87.980 | 38.927 | 13.760 | 25.007 | 5.139 |
| 32.133 | 66.533 | 38.240 | 21.274 | 41.575 | 15.527 |
| 35.939 | 64.849 | 14.606 | 16.335 | 13.331 | 7.765 |
| 94.061 | 164.618 | 67.828 | 40.536 | 39.822 | 22.828 |
| 24.373 | 31.984 | 29.400 | 13.838 | 27.849 | 20.528 |
| 24.054 | 41.694 | 20.733 | 22.952 | 30.385 | 15.213 |
| 48.004 | 26.509 | 31.914 | 36.538 | 9.208 | 7.965 |
| 11.097 | 24.811 | 8.344 | 11.187 | 23.557 | 16.183 |
| 59.784 | 77.949 | 24.957 | 24.314 | 1.851 | 7.666 |
| 22.094 | 64.159 | 6.850 | 5.495 | 0.000 | 9.652 |
| 50.334 | 13.213 | 17.335 | 19.717 | 23.163 | 4.706 |
| 0.000 | 14.004 | 10.790 | 15.934 | 18.383 | 2.804 |
| 55.925 | 80.380 | 23.813 | 8.800 | 0.000 | 1.912 |
| 49.181 | 85.632 | 18.827 | 24.926 | 29.064 | 9.604 |
| 51.383 | 68.465 | 43.831 | 29.109 | 17.347 | 0.000 |

Table 5 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 7.140 |
| 13.023 | 9.840 | 9.380 | 7.824 | 15.630 | 37.433 |
| 11.036 | 7.895 | 9.618 | 7.007 | 11.631 | 8.743 |
| 2.758 | 1.948 | 2.142 | 7:441 | 17.900 | 15.406 |
| 3.370 | 3.351 | 2.221 | 0.211 | 0.000 | 21.428 |
| 10.470 | 7.080 | 4.227 | 0.551 | 0.253 | 15.141 |
| 13.916 | 10.509 | 8.888 | 2.115 | 0.690 | 0.000 |
| 10.223 | 8.164 | 6.526 | 5.330 | 10.997 | 29.519 |
| 0.636 | 2.475 | 3.727 | 2.077 | 5.914 | 2.636 |
| 16.645 | 13.183 | 10.900 | 8.863 | 13.952 | 17.614 |
| 10.704 | 8.671 | 7.342 | 0.189 | 0.338 | 8.214 |
| 13.952 | 11.850 | 7.861 | 9.624 | 14.808 | 31.940 |
| 3.272 | 1.079 | 2.840 | 3.989 | 5.805 | 11.229 |
| 13.057 | 8.271 | 7.545 | 6.961 | 18.105 | 14.123 |
| 7.076 | 4.130 | 2.723 | 4.178 | 6.235 | 5.723 |
| 5.728 | 3.060 | 3.280 | 6.250 | 15.100 | 14.379 |
| 7.145 | 6.630 | 4.558 | 6.733 | 13.183 | 11.167 |
| 0.286 | 1.392 | 0.389 | 4.573 | 1.467 | 21.091 |
| 12.471 | 9.683 | 8.394 | 0.000 | 0.000 | 9.855 |
| 0.000 | 0.000 | 1.229 | 3.192 | 2.920 | 0.000 |
| 7.447 | 6.704 | 4.091 | 0.907 | 6.027 | 8.958 |
| 11.123 | 6.972 | 6.876 | 5.554 | 17.850 | 26.937 |

Table 5 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 42.314 | 78.633 | 54.043 | 47.838 | 41.838 | 21.216 |
| 85.128 | 54.754 | 7.885 | 31.608 | 26.102 | 14.094 |
| 50.696 | 49.589 | 34.808 | 34.129 | 40.997 | 8.842 |
| 40.014 | 40.539 | 23.958 | 22.333 | 36.837 | 10.044 |
| 15.536 | 31.849 | 13.939 | 25.002 | 21.917 | 21.059 |
| 58.193 | 46.595 | 8.579 | 34.303 | 48.532 | 17.667 |
| 0.000 | 0.000 | 0.000 | 24.215 | 20.933 | 11. 658 |
| 37.925 | 0.000 | 5.161 | 0.000 | 2.110 | 6.247 |
| 4.059 | 27.375 | 32.740 | 47.700 | 51.068 | 18.784 |
| 47.309. | 97.005 | 42.186 | 19.996 | 12.423 | 13.839 |
| 25.445 | 15.950 | 15.268 | 35.154 | 49.541 | 17.995 |
| 48.006 | 38.410 | 28.709 | 36.023 | 23.752 | 5.727 |
| 46.541 | 54.759 | 29.881 | 27.494 | 40.174 | 16.813 |
| 51.618 | 62.171 | 23.220 | 26.924 | 26.268 | 12.988 |
| 41.644 | 73.951 | 33.795 | 34.725 | 19.143 | 12.360 |
| 49.829 | 47.487 | 47.448 | 32.207 | 21.756 | 8.091 |
| 52.247 | 55.409 | 25.052 | 9.098 | 29.096 | 6.659 |
| 67.279 | 79.071 | 61.764 | 58.591 | 40.0687 | 16.357 |
| 53.450 | 58.572 | 20.862 | 22.521 | 21.531 | 6.377 |
| 0.000 | 8.356 | 38.976 | 19.976 | '16.273 | 14.863 |
| 4.046 | 27.392 | 23.909 | 29.726 | 11.595 | 12.552 |
| 69.455 | 62.638 | 16.753 | 4.175 | 14.033 | 8.011 |

Table 5 (Contd.)

| Jan | Feb | Mar | Apr. | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 6.. 184 | 2.730 | 3.211 | 1.866 | 5.593 | 21.577 |
| 8.122 | 6.145 | 2.742 | 2.156 | 5.374 | 4.651 |
| 2.238 | 0.000 | 0.456 | 1.211 | 0.000 | 0.000 |
| 1.966 | 1.130 | 0.000 | 0:000 | 0.000 | 0.000 |
| 0.000 | 0.000 | 0.0000 | 0.000 | 0.000 | 0.000 |
| 15.866 | - 11.605- | 7.275 | 6.896 | 9.140 | 45.760 |
| 4.765 | 3.010 | 4.606 | 2.867 | 1.671 | 22.671 |
| 2.042 | 0.654 | 2.372 | 6.163 | 6.603 | 0.000 |
| 5.737 | $4.631{ }^{\circ}$ | 2.705 | 6.914 | 6.432 | 22.668 |
| 1.636 | 0.000 | 0.000 | 0.000 | 2.216 | 13.612 |
| 13.387 | 10.071 | 5.351 | 4.616 | 4.547 | 26.307 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 27.872 |
| 18.069 | 12.228 | 9.051 | 7.028 | 10.755 | 23.037 |
| 12.529 | 11.123 | 11.286 | 12.418 | 21.105 | 23.475 |
| 10.985 | 6.691 | 6.760 | 6.805 | 14.753 | 23.202 |
| 15.417 | 10.534 | 6.967 | 2.327 | 5.959 | 23.742 |
| 5.232 | 2.818 | 4.930 | 2.952 | 6.360 | 26.269 |
| 10.849. | 7.178 | 7.908 | 5.930 | 9.327 | 28.192 |
| 8.528 | 5.827 | 6.807 | 6.911 | 13.822 | 34.119 |
| 9.948 | 7.363 | 4.802 | 0.000 | 0.000 | 20.472 |
| 4.099 | 3.141 | 0.000 | 0.000 | 0.000 | 17.131 |
| 11.649 | 9.051 | 8.660 | 5.042 | 5.659 | '13.327 |
| 11.755 | 10.292 | 6.882 | 4.021 | 9.109 | 15.716 |

Table 5. (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 51.507 | 51.074 | 58.752 | 46.874 | 26.698 | 9.982 |
| 39.686 | 83.481 | 21.542 | 3.486 | 0.000 | 6.827 |
| 19.103 | 0.000 | 4.182 | 32.095 | 12.024 | 4.029 |
| 8.779 | 37.595 | 26.605 | 21.572 | 6.513 | 2.438 |
| 37.416 | 12.478 | 17.822 | 3.049 | 24.201 | 18.378 |
| 103.368 | 113.950 | 60.138 | 21.825 | 42.129 | 7.983 |
| 56.088 | 91.982 | 38.187 | 39.312 | 18.046 | 4.062 |
| 0.000 | 50.621 | 10.856 | 22.400 | 29.036 | 8.636 |
| 82.193 | 111.656 | 58.067 | 30.652 | 9.198 | 4.460 |
| 33.572 | 72.590 | 56.048 | 46.477 | 19.108 | 15.368 |
| 38.485 | 13.440 | 23.574 | 10.977 | 4.165 | 0.053 |
| 37.699 | 61.686 | 63.880 | 31.607 | 41.491 | 25.068 |
| 42.064 | 69.036 | $-46: 437$ | 43.029 | 21.916 | 16.133 |
| 41.744 | 4.770 | 26.616 | 41.335 | 36.931 | 11.678 |
| 72.531 | 84.003 | 53.080 | 20.794 | 37.101 | 17.218 |
| 50.986 | 74.591 | 38.538 | 34.588 | 15.244 | 10.331 |
| $\angle 8.706$ | 33.322 | 53.857 | 52.598 | 31.116 | 16.148 |
| 88.444 | 97.265 | 38.159 | 26.296 | 24.734 | 7.795 |
| 44.349 | 47.115 | 13.351 | 12.836 | 13.086 | 12.717 |
| 39.998 | 76.416 | 21.886 | 22.541 | 52.742 | 6.416 |
| 28.933 | 57.093 | 29.358 | 6.633 | 20.258 | 17.221 |
| 12.603 | 57.189 | 52.461 | 25.075 | 13.302 | 16.823 |
| 52.026 | 66.754 | 7.126 | 26.168 | 0.000 | 6.952 |

Table 5 (Contd.)

| Fan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 4.165 | 4.004 | 4.533 | 1.791 | 4.157 | 16.782 |
| 12.154 | 7.631 | 7.330 | 6.901 | 16.397 | 36.030 |
| 0.511 | 1.006 | 0.000 | 1.405 | 2.678 | 20.791 |
| 9.555 | 7.917 | 6.625 | 4.761 | 7.461 | 12.047 |
| 0.000 | 0.035 | 0.000 | 4.511 | 13.018 | 39.553 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.043 |
| 15.201 | 10.473 | 9.685 | 7.736 | 12.075 | 11.228 |
| 0.042 | 0.000 | 0.000 | 1.462 | 2.573 | 22.115 |
| 9.053 | 7.799 | 6.642 | 5.820 | 7.135 | 22.747 |
| 4.432 | 5.579 | 3.045 | 2.985 | 1.644 | 14.348 |

Means
7.1664
5.3633
4.4477
3.6149
6.1955
16.2151

Standard deviations
$5.1702 \quad 3.9439$
3.3096
2.9244
5.6444
10.9549

Skewness co-efficient
0.1595
0.1967
0.2920
0.4885
0.7309
0.2594

Slopes
0.8531
0.7399
0.7581
0.5360
1.7190
0.9513

Correlations with previous month
0.9147
0.9699
0.9034
0.6066
0.8891
0.4910

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 76.464 | 82.172 | 23.767 | 24.972 | 1.556 | 12.024 |
| 54.514 | 109.198 | 41.471 | 55.519 | 46.304 | 5.012 |
| 59.714 | 110.531 | 47.393 | 40.1 .43 | 9.953 | 9.477 |
| 12.910 | 39.078 | 28.893 | 22.510 | 10.807 | 5.741 |
| 71.257 | 60.237 | 28.480 | 37.240 | 9.050 | 3.358 |
| 18.055 | 56.411 | 35.365 | 35.055 | 44.535 | 19.830 |
| 35.292 | $15.884^{-}$ | 0.000 | 2.549 | 0.000 | 6.410 |
| 65.315 | 56.094 | 37.429 | 14.023 | 19.424 | 14.048 |
| 42.383 | 35.733 | 20.328 | 7.377 | 1.091 | 9.386 |
| 1.618 | 0.000 | 13.890 | 20.742 | 25.262 | 9.542 |
| 60.278 | 87.495 | 27.540 | 43.058 | 19.619 | 13.252 |

Means
$\begin{array}{llllll}42.0324 & 55.3094 & 29.5272 & 25.2358 & 23.5798 & 10.7857\end{array}$
Standard deviations

| 23.6905 | 31.1307 | 16.5585 | 12.5033 | 14.4223 | 5.5404 |
| :--- | :--- | :--- | :--- | :--- | :--- |

Sknewness co-efficient
0.1629
0.4588
0.2817
0.2059
0.2693
0.1707

Slopes

1. 3402
0.8368
0.2725
0.4263
0.4433
0.1733

Correlations with previous month
0.6198
0.6368
0.5123
0.5645
0.3843
0.4511

Table $\sigma$ Generated flows of location two for 100 years (no transformation)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 15.025 | 9.234 | 9.000 | 13.054 | 35.804 | 170.516 |
| 0.000 | 0.000 | 0.000 | 0.0 .00 | 0.000 | 150.429 |
| 4.949 | 2.466 | 1.177 | 5.883 | 21.451 | 115.164 |
| 0.0 .00 | 0.000 | 0.000 | 0.000 | 3.893 | 0.000 |
| 12.297 | 8.304 | 10.551 | 16.404 | 16.015 | 146.810 |
| 10.536 | 5.647 | 4.132 | 7.525 | 15.744 | 196.192 |
| 15.158 | 10.536 | 9.187 | 8.158 | 18.036 | 83.391 |
| 9.747 | 6.952 | 4.941 | 6.974 | 11.966 | 98.436 |
| 4.788 | 2.414 | 0.852 | 0.000 | 0.929 | 0.000 |
| 16.472 | 11.960 | 11.192 | 15.177 | 34.432 | 4.275 |
| '9.718 | 7.657 | 5.762 | 2.819 | 0.488 | 192.611 |
| 12.698 | 8.302 | 4.824 | 8.743 | 13.324 | 65.909 |
| 1.512 | 0.808 | 0.791 | 3.787 | 2.378 | 133.359 |
| 14.615 | 10.260 | 8.513 | 7.189 | 8.283 | 10.754 |
| 3.141 | 0.000 | 0.000 | 0.853 | 3.127 | 144.289 |
| 1.480 | 1.930 | 0.678 | 4.759 | 5.344 | 70.555 |
| 13.763 | 10.680 | 10.656 | 13.400 | 49.036 | 124.183 |
| 11.126 | 6.155 | 3.982 | 4.455 | 9.608 | 0.000 |
| 4.486 | 1.281 | 0.118 | 0.000 | 5.994 | 95.604 |
| 9.299 | 6.421 | 4.773 | 3.139 | 10.185 | 24.956 |
| 15.115 | 11.001 | 9.639 | 3.457 | 2.456 | 74.334 |
| 8.525 | 3.578 | 4.776 | 6.632 | 6.698 | 102.200 |


| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 236.404 | 451.954 | 135.899 | 83.673 | 77.753 | 15.047 |
| 262.189 | 89.033 | 85.542 | 59.419 | 2.276 | 12.674 |
| 326.303 | 299.098 | 114.284 | 89.972 | 93.228 | 3.733 |
| 179.420 | 308.399 | 58.885 | 38.181 | 139.599 | 36.939 |
| 102.324 | 48.135 | 127.411 | 60.453 | 42.185 | 7.530 |
| 393.115 | 324.214 | 63.948 | 58.311 | 138.206 | 26.012 |
| 271.136 | 265.628 | 121.790 | 49.960 | 106.851 | 11.162 |
| 294.797 | 317.641 | 137.905 | 60.153 | 0.000 | 10.124 |
| 250.466 | 140.687 | 62.990 | 50.106 | 171.760 | 24.361 |
| 236.240 | 203.818 | 7.635 | 63.132 | 160.646 | 25.951 |
| 121.415 | 36.540 | 19.271 | 51.359 | 48.271 | 22.899 |
| 35.075 | 268.677 | 68.247 | 36.629 | 258.325 | 10.886 |
| 159.440 | 95.090 | 105.374 | 89.338 | 63.123 | 19.051 |
| 253.735 | 214.087 | 4.483 | 62.260 | 45.499 | 24.808 |
| 17.579 | 44.882 | 43.655 | 68.796 | 239.598 | 19.594 |
| 226.010 | 298.468 | 78.094 | 58.109 | 21.580 | 23.401 |
| 169.2 .39 | 19.844 | 0.000 | 16.462 | 172.917 | 19.424 |
| 180.271 | 270.192 | 69.579 | 87.271 | 40.657 | 19.870 |
| 279.571 | 177.667 | 74.447 | 57.848 | 124.408 | 7.322 |
| 134.761 | 196.955 | 56.217 | 60.421 | 89.975 | 24.179 |
| 346.033 | 205.509 | 138.120 | 92.880 | 190.017 | 23.999 |
| 181.442 | 182.877 | 19.347 | 12.317 | 0.000 | 5.388 |

Table 6 (Contd.)

| Jan | Feb | Max | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 7.738 | 2.720 | 0.797 | 0.000 | 12.660 | 84.955 |
| 11.099 | 8.384 | 7.991 | 6.183 | 16.819 | 22.864 |
| 3.034 | 2.875 | 1.251 | 3.420 | 15.313 | 6.127 |
| 0.000 | 0.000 | 0.000 | 0.925 | 5.955 | 0.000 |
| 15.648 | 12.092 | 12.030 | 9.360 | 14.362 | 133.176 |
| 23.071 | 6.409 | 15.504 | 15.969 | 22.740 | 170.169 |
| 2.794 | 2.244 | 1.766 | 0.057 | 14.403 | 77.053 |
| 18.347 | 5.403 | 14.515 | 18.033 | 12.106 | 129.467 |
| 0.000 | 0.000 | 0.000 | 0.000 | 4.453 | 35.679 |
| 21.248 | 16.692 | 14.938 | 11.401 | 0.000 | 77.148 |
| 5.405 | 2.550 | 2.231 | 12.311 | 25.808 | 205.282 |
| 14.019 | 10.726 | 9.101 | 0.000 | 2.584 | 66.956 |
| 17.425 | 11.842 | 10.073 | 11.234 | 13.760 | 0.000 |
| 6.951 | 3.055 | 2.459 | 3.397 | 3.920 | 168.007 |
| 17.113 | 11.859 | 12.034 | 12.841 | 12.489 | 0.000 |
| 20.795 | 16.910 | 17.110 | 13.538 | 22.566 | 127.865 |
| 6.396 | 1.966 | 1.254 | 5.332 | 5.328 | 148.874 |
| 14.3 .25 | 10.507 | 9.519 | 12.268 | 23.530 | 148.330 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 94.784 |
| 0.000 | 0.000 | 0.000 | 0.000. | 0.000 | 81.532 |
| 7.315 | 5.659 | 5.511 | 10.099 | 17.409 | 47.317 |
| 0.000 | 0.000 | 0.000 | 6.223 | 14.805 | 143.531 |

Table 6 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 284.508 | 279.171 | 155.864 | 97.096 | 179.829 | 4.889 |
| 151. 335 | 97.350 | 53.659 | 77.314 | 59.901 | 17.063 |
| 146.983 | 324.336 | . 149.359 | 87.680 | 53.632 | 0.000 |
| 206.387 | 290.658 | 135.883 | 96.295 | 41.396 | 0.000 |
| 407.024 | 157.643 | 40.662 | 60.387 | 61.693 | 29.255 |
| 167.687 | 98.337 | 77.002 | 50.358 | 104.498 | 5.269 |
| 392.706 | 404.955 | 109.191 | 53.967 | 19.488 | 26.860 |
| 396.360 , | 286.462 | 105.871 | 99.111 | 107.008 | 6.612 |
| 223.320 | 284.686 | 116.989 | 63.173 | 177.197 | 25.159 |
| 221.599 | 264.869 | 53.348 | 52.709 | 42.747 | 14.124 |
| 351.540 | 555.259 | 202.796 | 110.588 | 129.689 | 39.162 |
| 191.103 | 151.345 | 80.566 | 40.039 | 121.450 | 39.112 |
| 286.785 | 239.511 | 76.341 | 71.241 | 116.937 | 26.352 |
| 188.693 | 52.820 | 63.932 | 83.929 | 0.000 | 13.144 |
| 142.502 | 139.815 | 29.028 | 37.285 | 105.123 | 30.853 |
| 280.171 | 272.199 | 73.183 | 67.646 | 0.000 | 15.147 |
| 74.733 | 233.274 | 25.836 | 24.037 | 0.000 | 22.226 |
| 210.279 | 1.458 | 21.815 | 42.974 | 84.737 | 5.359 |
| 25.003 | 73.620 | 24.182 | 43.365 | 68.680 | 2.573 |
| 317.434 | 312.821 | 79.662 | 34.682 | 0.000 | 5.712 |
| 283.902 | 339.181 | 70.924 | 75.986 | 106.220 | 14.354 |
| 182.426 | 211.500 | 110.262 | 71.788 | 36.679 | 0.000 |

Contd.

Têble 6 (Contd.)

| . Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.000. | 0.000 | 0.000 | 0.000 | 0.000 | 76.081 |
| 4.880 | 2.382 | 2.605 | 7.370 | 24;015 | 191.583 |
| 13.960 | 9.270 | 10.633 | 12.824 | 21.349 | 14.381 |
| 0.000 | 0.000 | 0.000 | 6.932 | 33.394 | 37.741 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 150.076 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 96.346 |
| 14.102 | 9.898 | 9.404 | 5.048 | 2.275 | 0.000 |
| 16.748 | 12.692 | 11.819 | 13.505 | 29.369 | 173.892 |
| 1.214 | 2.140 | 2.404 | 2.633 | 17.475 | 2.997 |
| 19.253 | 14.848 | 14.287 | 17.785 | 24.704 | 65.863 |
| 14.862 | 11.296 | 10.741 | 4.391 | 11.080 | 68.131 |
| 13.496 | 14.086 | 9.194 | 16.696 | 22.082 | 155.991 |
| 7.021 | 2.508 | 2.903 | 6.505 | 10.943 | 53.962 |
| 14.004 | 7.799 | 7.580 | 11.602 | 42.264 | 40.172 |
| 4.743 | 0.810 | 0.000 | 4.007 | 8.420 | 9.455 |
| 2.194 | 0.000 | 0.000 | 5.678 | 29.035 | 42.273 |
| 14.112 | 11.601 | 10.210 | 15.582 | 31.418 | 35.624 |
| 0.000 | 0.000 | 0.000 | 3.652 | 0.000 | 119.510 |
| 11.956 | 8.508 | 8.120 | 0.109 | 2.483 | 83.437 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 3.247 | 2.517 | 0.810 | 0.000 | 20.496 | 50.409 |
| 18.106 | 11.392 | 11.382 | 13.221 | 51.168 | 143.320 |

```
Table 6 (Contd.)
```

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 276.194 | 328.333 | 60.860 | 126.831 | 125.238 | 34.583 |
| 311.623 | 112.184 | 1.888 | 74.742 | 76.186 | 23.759 |
| 294.611 | 191.513 | 93.965 | 88.082 | 147.943 | 9.572 |
| 200.647 | 141.688 | 58.996 | 57.694 | 150.109 | 14.108 |
| 60.229 | 114.046 | 31.824 | 64.648 | 68.525 | 40.164 |
| 306.433 | 161.323 | 21.843 | 89.419 | 186.215 | 27.131 |
| 46.433 | 0.000 | 0.000 | 60.410 | 64.868 | 20.244 |
| 123.431 | 0.000 | 0.000 | 0.000 | 17.619 | 14.551 |
| 98.381 | 150.826 | 91.684 | 122.414 | 172.383 | 27.694 |
| 228.424 | 364.440 | 129.314 | 60.626 | 30.687 | 26.939 |
| 182.217 | 77.610 | 35.292 | 88.983 | 189.457 | 27.553 |
| 154.109 | 84.644 | 56.999 | 83.658 | 55.169 | 5.771 |
| 265.200 | 211.386 | 83.691 | 73.755 | 157.179 | 27.513 |
| 268.327 | 227.330 | 66.614 | 73.179 | 87.261 | 21.882 |
| 268.348 | 307.333 | 107.272 | 96.886 | 35.590 | 21.040 |
| 258.025 | 167.538 | 120.621 | 79.318 | 53.024 | 11.619 |
| 290.525 | 208.510 | 70.384 | 29.576 | 137.415 | 9.622 |
| 316.906 | 271.245 | 164.717 | 144.561 | 97.094 | 23.225 |
| 315.528 | 230.065 | 63.655 | 64.256 | 72.001 | 9.014 |
| 77.809 | 98.331 | 105.123 | 53.688 | 49.833 | 28.413 |
| 65.582 | 134.731 | 65.178 | 78.390 | 6.455 | 23.302 |
| 293.383 | 185.183 | 38.801 | 14.007 | 59.927 | 15.735 |

Table 6 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 13.038 | 6.677 | 6.439 | 6.111 | 21.648 | 235.372 |
| 12.554 | 8.746 | 6.401 | 6.837 | 20.122 | 24.179 |
| 6.598 | 0.823 | 0.583 | . 2.081 | 0.000 | 0.000 |
| 7.317 | 4.101 | 2.034 | 0.000 | 0.000 | 0.000 |
| 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 8.444 |
| 21.182 | 15.171 | 12.994 | 16.300 | 17.548 | 281.504 |
| 6.484 | 3.072 | 3.645 | 4.244 | 0.467 | 144.745 |
| 6.823 | 3.012 | 3.312 | 10.393 | 6.063 | 0.000 |
| 8.943 | 6.201 | 4.634 | 12.398 | 3.630 | 118.857 |
| 5.814 | 1.356 | 0.000 | 0.714 | 14.289 | 98.143 |
| 18.314 | 13.301 | 10.640 | 12.264 | 9.907 | 165.049 |
| 6.015 | 1.329 | 1.282 | 0.000 | 13.352 | 214.654 |
| 12.932 | 7.058 | 5.791 | 9.131 | 13.906 | 108.480 |
| 14.354 | 12.253 | 13.040 | 21.715 | -33.820 | 73.854 |
| 17.214 | 10.440 | 10.503 | 14.404 | 34.988 | 114.138 |
| 20.519 | 13.701 | 11.883 | 8.809 | 23.479 | 157.594 |
| 4.774 | 0.970 | 1.871 | 2.636 | 14.100 | 159.200 |
| 8.495 | 4.068 | 4.682 | 7.359 | 13.102 | 152.176 |
| 18.693 | 12.958 | 13.491 | 17.070 | 34.346 | 164.853 |
| 14.926 | 10.448 | 8.846 | 3.519 | 5.90 | 161.076 |
| 6.777 | 4.134 | 0.870 | 1.520 | 0.000 | 134.362 |
| 11.263 | 7.939 | 8.063 | 8.497 | 6.774 | 63.510 |

Table 6 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 244.214 | 170.150 | 147.521 | 112.351 | 48.695 | 13.263 |
| 268.828 | 352.940 | 82.762 | 26.213 | 0.000 | 20.834 |
| 256.840 | 0.000 | 0.311 | 79.950 | 3.543 | 4.678 |
| 202.113 | 223.158 | 90.873 | 67.957 | 0.000 | 0.396 |
| 308.155 | .87.682 | 46.559 | 13.452 | 124.379 | 36.264 |
| 366.244 | 324.792 | 153.294 | 52.839 | 177.931 | 8.765 |
| 255.131 | 329.208 | 112.959 | 104.879 | 20.517 | 2.951 |
| 79.497 | 255.862 | 50.351 | 70.790 | 111.218 | 12.547 |
| 381.287 | 389.808 | 166.905 | 82.983 | 0.000 | 6.290 |
| . 193.033 | 290.065 | 159.412 | 120.311 | 11.422 | 26.270 |
| 146.095 | 8.171 | 39.145 | 21.773 | 5.070 | 0.000 |
| '142.008 | 206.966 | 163.639 | 76.309 | 155.043 | 44.530 |
| 174.312 | 239.328 | 123.900 | 108.196 | 32.380 | 27.742 |
| 162.437 | 0.000 | 42.045 | 92.341 | 111.579 | 15.593 |
| 327.982 | 280.369 | 142.274 | 54.664 | 154.425 | 29.601 |
| 224.878 | 258.916 | 105.840 | 89.796 | 15.341 | $17.376^{\prime}$ |
| 95.816 | 96.006 | 126.387 | 122.836 | 59.530 | 25.091 |
| 382.489 | 311.464 | 104.863 | 69.854 | 80.520 | 11.047 |
| 129.138 | 119.663 | 22.367 | 31.774 | 47.450 | 25.099 |
| 192.324 | 285.105 | 69.869 | 65.819 | 231.741 | 3.439 |
| 153.494 | 221.506 | 83.633 | 24.126 | 97.194 | 34.136 |
| 81.947 | 238.223 | 246.099 | 67.281 | 24.522 | 32.637 |

Table 6 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 12.072 | 10.086 | 8.356 | 8.374 | 24.233 | 82.928 |
| 9.394 | 7.313 | 7.296 | 5.810 | 16.810 | 11.334 |
| 22.906 | 15.145 | 15.078 | 18.043 | 44.326 | 205.889 |
| 0.000 | 0.000 | 0.000 | 0.000 | 6.254 | 133.528 |
| 19.005 | 14.878 | 14.189 | 14.611 | 21.788 | 64.518 |
| 0.000 | 0.000 | 0.000 | 3.666 | 29.300 | 230.470 |
| 0.214 | 0.0 .00 | 0.000 | 0.000 | 4.022 | 16.027 |
| 14.049 | 8.546 | 8.613 | 12.139 | 17.975 | 23.979 |
| 0.000 | 0.000 | 0.000 | 0.088 | 6.531 | 143.779 |
| 9.413 | 7.379 | 6.800 | 9.881 | 9.197 | 122.846 |
| 6.148 | 6.541 | 4.654 | 6.365 | 2.205 | 89.687 |
| 3.872 | 2.004 | 0.507 | 1.586 | 18.844 | 39.871 |
| Means |  |  |  |  |  |

9.2104
6.1587
5.5289
6.7900
14.0978
93.5924

Standard deviations
6.7285
5.1584
4.9975
5.7464
12.0855
65.9466

Skewness co-efficient
0.1422
0.3374
0.4356
0.4865
0.9051
0.2395

Slopes
0.3258
0.7432
0.9507
0.9362
1.4022
1.1359

Correlations with previous month
0.5169
0.9694
0.9813
0.8142
0.6667
0.2082

Table 6 (Conta.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 268.626 | 245.027 | 28.061 | 74.518 | 0.000 | 14.088 |
| 390.605 | 291.343 | 72.689 | 70.540 | 0.000 | 24.490 |
| 169.785 | 362.791 | 119.504 | 142.690 | 132.454 | 0.000 |
| 283.749 | 408.126 | 145.682 | 109.934 | 0.000 | 15.959 |
| 92.357 | 167.948 | 79.328 | 63.029 | 16.896 | 9.574 |
| 235.564 | 141.041 | 57.951 | 88.767 | 0.000 | 3.162 |
| 189.212 | 270.775 | 112.330 | 97.967 | 164.837 | 32.445 |
| 202.180 | 56.038 | 0.000 | 10.337 | 0.000 | 16.606 |
| 305.185 | 177.222 | 92.690 | 35.668 | 77.575 | 26.691 |
| 180.913 | 104.682 | 42.962 | 19.016 | 0.000 | 20.683 |
| 25.191 | 5.332 | 23.085 | 50.460 | 93.845 | 15.271 |
| 355.214 | 330.515 | 91.827 | 117.991 | 21.400 | 22.015 |
| Means |  |  |  |  |  |
| 219.5857 | 205.5499 | 81.2822 | 67.4815 | 79.0723 | 18.0357 |
| Standard deviations |  |  |  |  |  |
| 95.7561 | 114.5880 | 46.8976 | 29.9427 | 64.9309 | 10.6412 |

Skewness co-efficient

| -0.1112 | 0.0838 | 0.1831 | 0.1551 | 0.5844 | 0.1613 |
| :--- | :--- | :--- | :--- | :--- | :--- |

Slopes
0.1471
0.6181
0.2678
0.3559
0.1348
0.0360

Correlations with previous month
0.1013
0.5165
0.6544
0.5574
0.0622
0.2198

Table 7 Generated flows of location three for 100 years (No transformation)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 53.183 | 27.210 | 20.259 | 24.992 | 95.262 | 521.574 |
| 16.058 | 0.000 | 0.000 | 0.000 | 0.000 | 572.476 |
| $35.985^{\circ}$ | 20.099 | 13.780 | 15.368 | 62.966 | 369.741 |
| 23.303 | 19.454 | 12.258 | 3.709 | 47.079 | 0.000 |
| 34.109 | 18.084 | 20.416 | 26.864 | 40.215 | 437.878 |
| 50.846 | 25.804 | 15.702 | 17.677 | 45.317 | 669.430 |
| 47.497 | 27.519 | 17.460 | 17.060 | 48.657 | 262.150 |
| 46.125 | 29.664 | 17.156 | 18.634 | 38.095 | 336.484 |
| 37.657 | 21.624 | 12.513 | 8.260 | 18.135 | 0.000 |
| 50.983 | 31.395 | 21.860 | 27.374 | 88.303 | 0.000 |
| 35.729 | 24.766 | 13.945 | 10.311 | 6.051 | 699.051 |
| 45.172 | 24.971 | 9.792 | 10.175 | 22.321 | 200.768 |
| 27.356 | 18.087 | 14.419 | 15.134 | -16.010 | 488.802 |
| 51.652 | 31.204 | 19.030 | 18.866 | 27.440 | 35.649 |
| 23.680 | 1.458 | 0.000 | 0.000 | 0.000 | 504.984 |
| 21.705 | 18.251 | 10.918 | 11.329 | 14.936 | 250.880 |
| 47.361 | 32.249 | 24.484 | 29.853 | 139.127 | 329.718 |
| 42.903 | 20.066 | 9.779 | 7.236 | 21.235 | 0.000 |
| 29.862 | 12.568 | 7.051 | 0.092 | 24.159 | 344.281 |
| 47.550 | 30.090 | 18.444 | 17.362 | 43.656 | 91.546 |
| 49.039 | 30.527 | 19.603 | 15.808 | 18.412 | 281.839 |
| 34.214 | 31.991 | 13.095 | 12.962 | 15.227 | 356.198 |

Table 7 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 914.118 | 1650.962 | 455.722 | 300.842 | 253.479 | 78.260 |
| 1054.435 | 607.662 | 531.325 | 312.641 | 164.852 | 152.688 |
| 1436.978 | 1287.873 | 495.106 | 417.010 | 271.919 | 0.000 |
| 903.907 | 1308.546 | 246.430 | 176.560 | 332.441 | 336.958 |
| 285.352 | 402.906 | 735.535 | 249.601 | 212.734 | 9.070 |
| 1637.443 | 1347.200 | 254.754 | 295.319 | 321.844 | 172.019 |
| 1214.220 | 1178.028 | 553.143 | 148.677 | 291.577 | 0.000 |
| 1304.091 | 1333.178 | 581.607 | 174.965 | 125.166 | 160.755 |
| 1294.727 | 874.896 | 406.069 | 285.245 | 370.430 | 84.897 |
| 1173.101 | 1030.489 | 384.927 | 341.934 | 355.858 | 128.160 |
| 298.392 | 346.639 | 272.870 | 387.848 | 221.494 | 248.112 |
| 78.652 | 1061.650 | 303.075 | 153.768 | 475.926 | 0.000 |
| 578.449 | 578.394 | 606.788 | 469.458 | 235.802 | 165.308 |
| 1237.546 | 1061.763 | 89.754 | 453.904 | 217.250 | 283.750 |
| 0.000 | 343.536 | 368.620 | 454.959 | 451.024 | 0.000 |
| 1006.915 | 1254.344 | 334.708 | 273.363 | 188.170 | 297.284 |
| 659.875 | 377.163 | 134.009 | 233.535 | 375.115 | 1.291 |
| 939.308 | 1209.898 | 325.161 | 486.819 | 208.938 | 212.453 |
| 1230.869 | 914.853 | 417.734 | 304.863 | 312.506 | 0.000 |
| 628.591 | $933.320^{-}$ | 318.485 | 349.296 | 270.802 | 206.298 |
| 1589.618 | 1047.799 | 677.920 | 414.195 | 388.518 | 53.635 |
| 738.877 | 869.826 | 167.092 | 103.922 | 103.591 | 114.277 |

Table 7 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 47.246 | 20.755 | 10.908 | 6.015 | 47.795 | 293.856 |
| 52.444 | 35.535 | 25.822 | 27.618 | 68.919 | 71.967 |
| 20.454 | 21.985 | 12.611 | 12.131 | 48.599 | 2.500 |
| 28.472 | 16.151 | 8.322 | 9.505 | 26.300 | 0.000 |
| 66.837 | 46.070 | 34.376 | 39.007 | 70.103 | 475.395 |
| 62.81 .3 | 36.530 | 25.254 | 29.625 | 56.576 | 552.101 |
| 35.127 | 25.531 | 18.283 | 16.714 | 64.573 | 271.896 |
| 54.805 | 41.378 | 28.785 | 36.791 | 31.628 | 439.801 |
| 23.445 | 18.255 | 17.550 | 15.923 | 40.525 | 154.563 |
| 60.529 | 41.517 | 26.544 | 28.032 | 0.330 | 297.118 |
| 35.589 | 18.722 | 13.807 | 20.344 | -62.121 | 6665.676 |
| 36.407 | 23.587 | 13.874 | 3.967 | 13.389 | 254.203 |
| 43.716 | 22.683 | 12.844 | 12.701 | 19.453 | 0.000 |
| 30.031 | 11.788 | 8.054 | 5.092 | 5.282 | 594.104 |
| 61.683 | 36.906 | 28.403 | 33.752 | 44.846 | 0.000 |
| 56.492 | 40.765 | 31.326 | 34.754 | 72.433 | 417.359 |
| 37.756 | 15.075 | 10.092 | 10.277 | 11.296 | 524.657 |
| 49.723 | 31.604 | 21.393 | 25.525 | 64.305 | 477.709 |
| 14.847 | 9.821 | 2.166 | 0.000 | 0.000 | 390.165 |
| 16.810 | 8.168 | 5.622 | 1.207 | 0.000 | 335.032 |
| 46.001 | 32.185 | 24.034 | 30.122 | 61.761 | 149.151 |
| 19.310 | 4.913 | 6.118 | 8.835 | 32.589 | 476.778 |

Table 7 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1273.734 | 1222.839 | 690.748 | 392.346 | 375.703 | 0.000 |
| 715.164 | 653.003 | 388.843 | 486.280 | 233.205 | 137.249 |
| 721.422 | 1327.156 | 622.806 | 331:884 | 224.038 | 0.000 |
| 1036.237 | 1271.938 | 596.690 | 421.325 | 208.437 | 0.000 |
| 1800.207 | 905.817 | 293.262 | 388.628 | 236.780 | 331.303 |
| 571.450 | 573.086 | 479.255 | 264.832 | 289.091 | 0.000 |
| 1818.176 | 1658.794 | 395.331 | 169.953 | 185.716 | 356.473 |
| 1756.816 | 1280.967 | 472.425 | 103.460 | 290.729 | 0.000 |
| 1044.182 | 1233.179 | 516.910 | 239.613 | 375.496 | 90.443 |
| 971.473 | 1147.674 | 253.327 | 289.889 | 214.349 | 114.546 |
| 1423.766 | 1996.671 | 668.236 | 334.675 | 313.555 | 391.909 |
| 838.653 | 804.340 | 461.370 | 181.944 | 310.346 | 399.763 |
| 1624.049 | 1248.251 | 394.790 | 380.608 | 302.362 | 201. 250 |
| 670.932 | 450.186 | 460.373 | 518.174 | 135.711 | 195.593 |
| . 721.921 | 793.035 | 249.731 | 260.545 | 291.177 | 290.339 |
| 1189.477 | 1174.021 | 334.101 | 350.188 | 122.324 | 245.590 |
| 139.754 | 925.588 | 143.552 | 154.873 | 142.014 | 338.259 |
| 814.978 | 327.650 | 322.318 | 338.752 | 266.236 | 0.000 |
| 0.000 | 460.224 | 264.980 | 318.834 | 246.733 | 0.000 |
| 1433.368 | 1339.454 | 335.223 | 115.674 | 118.657 | 99.084 |
| 1331.323 | 1423.294 | 276.924 | 396.054 | 288.981 | 23.298 |
| 682.899 | 929.261 | 535.633 | 321.015 | 205.161 | 0.000 |

Table 7 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 230.031 | 9.089 | 8.572 | 2.348 | 14.337 | 333.004 |
| 20.122 | 8.338 | 7.789 | 7.879 | 53.078 | 618.316 |
| 47.007 | 26.082 | 23.793 | 28.460 | 61.134 | 12.317 |
| 23.394 | 10.723 | 7.465 | 11.100 | 86.056 | 56.180 |
| 20.880 | 13.363 | 7.522 | 2.382 | 0.000 | 569.408 |
| 6.480 | 0.000 | 0.000 | 0.000 | 0.000 | 351.196 |
| 43.992 | 25.790 | 18.534 | 15.822 | 12.692 | 0.000 |
| 55.352 | 36.507 | 25.272 | 30.198 | 84.204 | 556.190 |
| 26.649 | 23.487 | 18.831 | 19.120 | 68.622 | 0.000 |
| 54.683 | 36.423 | 26.093 | 33.095 | 61.750 | 177.985 |
| 47.181 | 31.163 | 22.191 | 19.333 | 45.250 | 240.087 |
| 42.396 | 30.936 | 18.461 | 25.397 | 45.464 | 495.513 |
| 44.439 | 20.102 | 16.746 | 19.112 | 37.552 | 183.913 |
| 43.814 | 18.074 | 13.684 | 15.875 | 103.320 | 35.297 |
| 28.608 | 9.087 | 4.250 | 2.460 | 11.610 | 16.441 |
| 24.282 | 5.748 | 4.379 | 4.824 | 67.754 | 78.055 |
| 55.611 | 40.696 | 26.869 | 35.183 | 91.221 | 63.188 |
| 20.518 | 15.070 | 8.181 | 9.598 | 0.000 | 465.323 |
| 42.933 | 26.382 | 19.228 | 13.617 | 25.943 | 320.510 |
| 18.543 | 5.391 | 5.903 | 4.359 | 0.000 | 0.000 |
| 21.472 | 14.857 | 7.262 | 1.806 | 59.897 | 142.903 |
| 56.787 | 28.502 | 21.829 | 25.600 | 138.776 | 386.339 |

Table 7 (Contd.)

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1236.183 | 1363.519 | 672.505 | 566.949 | 307.301 | 324.945 |
| 1248.397 | 683.722 | 150.708 | 559.527 | 253.393 | 220.795 |
| 1438.594 | 1019.116 | 499.064 | 466.253 | 338.371 | 0.000 |
| 944.966 | 806.080 | 379.192 | 339.514 | 343.732 | 0.000 |
| 60.416 | 564.506 | 263.929 | 434.923 | 244.752 | 497.901 |
| 1361.394 | 881.749 | 204.393 | 610.585 | 384.954 | 109.554 |
| 252.443 | 72.723 | 156.335 | 571.619 | 241.238 | 180.124 |
| 348.977 | 0.000 | 217.144 | 90.627 | 189.938 | 156.167 |
| 485.907 | 792.108 | 508.730 | 700.095 | 365.155 | 141.384 |
| 1034.501 | 1455.555 | 504.918 | 183.023 | 198.602 | 341.157 |
| 795.317 | 583.397 | 323.571 | 599.728 | 388.877 | 111.482 |
| 527.693 | 534.615 | 403.658 | 521.792 | 226.958 | 0.000 |
| 1227.135 | 1032.959 | 433.099 | 385.452 | 350.725 | 159.243 |
| 1278.928 | 1096.470 | 348.226 | 409.728 | 266.417 | 173.804 |
| 1313.728 | 1345.239 | 462.109 | 474.227 | 201.785 | 239.683 |
| 1219.652 | 91.1.759 | 629.481 | 364.628 | 224.278 | 59.785 |
| 1388.855 | 1054.388 | 381.303 | 122.331 | 330.503 | 0.000 |
| 1371.981 | 1193.108 | 734.743 | 688.109 | 271.896 | 184.294 |
| 1424.158 | 1095.875 | 332.139 | 355.879 | 248.720 | 0.000 |
| 472.180 | 662.395 | 612.174 | 238.588 | 222.631 | 335.525 |
| 253.615 | 696.867 | 400.782 | 462.213 | 168.458 | 319.405 |
| 1243.115 | 921.918 | 255.183 | 80.711 | 250.448 | 97.642 |

Table 7 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 50.417 | 21.675 | 16.216 | 15.612 | 63.164 | 440.369 |
| 51.273 | 31.564 | 17.644 | 18.167 | 60.655 | 52.716 |
| 35.463 | 8.472 | 6.604 | 3.352 | 0.000 | 0.000 |
| 46.297 | 26.542 | 14.712 | 11.221 | 0.000 | 0.000 |
| 13.740 | 4.019 | 2.878 | 0.000 | 0.000 | 104.061 |
| 53.529 | 30.861 | 17.682 | 21.373 | 27.506 | 946.306 |
| 40.099 | 20.683 | 17.658 | 17.984 | 13.784 | 536.727 |
| 46.238 | 23.925 | 19.254 | 25.410 | 21.316 | 0.000 |
| 43.463 | 27.359 | 16.692 | 22.656 | 3.414 | 420.150 |
| 42.157 | 17.804 | 9.881 | 7.193 | 46.601 | 331.226 |
| 55.226 | 33.892 | 18.525 | 20.852 | 18.522 | 565.146 |
| 46.803 | 20.497 | 15.812 | 12.632 | 59.279 | 759.032 |
| 30.281 | 8.639 | 4.013 | 1.982 | 9.347 | 336.935 |
| 45.645 | 35.081 | 28.759 | 40.793 | 86.897 | 182.455 |
| 58.974 | 29.275 | 22.571 | 28.186 | 93.726 | 325.009 |
| 56.261 | 29.380 | 17.571 | 15.867 | 59.836 | 506.788 |
| 32.377 | 12.362 | 12.518 | 10.932 | 45.830 | 547.372 |
| 34.722 | 14.297 | 13.176 | 13.731 | 32.041 | 515.433 |
| 65.407 | 38.917 | 30.846 | 39.510 | 101.573 | 620.515 |
| 48.438 | 28.589 | 17.539 | 13.611 | 23.423 | 577.144 |
| 43.723 | 26.436 | 11.375 | 9.165 | 0.000 | 517.557 |
| 34.190 | 19.951 | 15.973 | 16.022 | 14.607 | 218.479 |

```
Table 7 (Contd.)
```

| Jul | Aug | Sep | Oct | Nov | Dec |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1001.141 | 849.515 | 735.595 | 528.998 | 216.208 | 94.598 |
| 1295.419 | 1470.679 | 318.097 | 46.467 | 0.000 | 498.995 |
| 1388. 370 | 323.341 | 296.904 | 637.711 | 165.380 | 21.760 |
| 1055.271 | 1105.707 | 452.500 | 324.948 | 158.364 | 9.967 |
| 1497.852 | 719.562 | 377.362 | 86.845 | 316.297 | 347.800 |
| 1375.374 | 1279.990 | 633.606 | 95.288 | 376.953 | 0.000 |
| 1030.876 | 1312.120 | 457.365 | 508.255 | 182.873 | 0.000 |
| 454.373 | 1114.332 | 246.714 | 415.246 | 295.619 | 0.000 |
| 1696.502 | 1580.878 | 653.868 | 257.260 | 150.473 | 65.456 |
| 803.'97 | 1193.948 | 689.980 | 533.337 | 170.384 | 362.293 |
| 468.471 | 297.720 | 386.091 | 165.668 | 271.602 | . 0.000 |
| 368.034 | 844.969 | 762.252 | 252.520 | 347.428 | 438.667 |
| 700.095 | 1029.651 | 574.747 | 528.930 | 196.931 | 353.703 |
| 700.496 | 258.500 | 437.849 | 632.305 | 294.577 | 35.748 |
| 1452.953 | 1237.122 | 632.122 | 139.658 | 348:524 | 196.628 |
| 872.958 | 1084.945 | 480.380 | 437.055 | 177.930 | 210.636 |
| 229.512 | 529.663 | 690.975 | 648.497 | 228.625 | 270.237 |
| 1653.678 | 1331.898 | 445.237 | 300.138 | 258.242 | 8.888 |
| 345.772 | 598.572 | 220.520 | 236.499 | 222.002 | 284.164 |
| 698.535 | 1137.091 | 300.237 | 339.004 | 441.444 | 0.000 |
| 543.847 | 943.281 | 410.174 | 55.000 | 282.253 | 355.171 |
| 309.399 | 999.441 | 668.680 | 220.579 | 190.598 | 443.148 |

Table 7 (Contd.)

| Jan | Feb | Mar | Apr | May | Jun |
| :---: | ---: | ---: | ---: | ---: | ---: |
| 37.629 | 28.059 | 16.806 | 16.929 | 65.108 | 243.641 |
| 45.029 | 31.303 | 23.776 | 25.021 | 65.899 | 382.146 |
| 66.581 | 35.055 | 26.455 | 33.245 | 116.161 | 622.115 |
| 29.969 | 19.326 | 9.505 | 8.275 | 30.572 | 482.690 |
| 63.856 | 44.035 | 31.237 | 37.543 | 71.261 | 196.275 |
| 22.576 | 12.627 | 6.534 | 7.853 | 80.045 | 752.912 |
| 32.520 | 14.612 | 5.700 | 0.549 | 22.726 | 71.599 |
| 40.572 | 18.361 | 14.681 | 16.947 | 35.200 | 40.430 |
| 22.933 | 9.794 | 4.170 | 1.187 | 17.141 | 505.698 |
| 35.402 | 24.419 | 17.279 | 19.885 | 22.801 | 423.275 |
| 33.255 | 29.722 | 17.533 | 18.842 | 13.076 | 332.688 |
| 31.074 | 18.061 | 10.116 | 7.764 | 57.431 | 111.792 |

Means

| 39.6479 | 22.6839 | $15.4268 \quad 16.0435$ | 41.2701 | 314.0305 |
| :--- | :--- | :--- | :--- | :--- | :--- |

Standard deviations

| 13.7037 | 10.5161 | 7.8194 | 10.8064 | 32.3678 | 227.2364 |
| :--- | :--- | :--- | :--- | :--- | :--- |

Skewness co-efficient
$-0.1134$
$-0.0705$
0.1540
0.3955
0.7435
0.1782

Slopes
0.0119
0.6791
0.6946
1.3183
1.7962
0.0292

Correlations with previous month
. 0.1245
0.8849
0.9342
0.9539
0.5997
0.0042

```
Table 7 (Contd.)
```

| Jul | Aug | Sep | Oct | Nov | Dec |
| ---: | ---: | ---: | ---: | ---: | ---: |
| 1205.067 | 1117.516 | 162.951 | 483.493 | 95.540 | 261.840 |
| 1755.859 | 1303.211 | 325.478 | 368.254 | 118.803 | 401.249 |
| 534.296 | 1329.849 | 448.943 | 733.691 | 314.954 | 0.000 |
| 1191.519 | 1568.066 | 538.949 | 465.768 | 130.507 | 245.770 |
| 362.928 | 800.420 | 436.251 | 316.098 | 182.357 | 80.401 |
| 813.372 | 699.472 | 362.417 | 541.261 | 131.334 | 39.033 |
| 908.896 | 1186.144 | 507.108 | 478.325 | 357.800 | 228.802 |
| 969.148 | 562.778 | 127.080 | 183.072 | 113.671 | 283.763 |
| 1283.059 | 897.927 | 495.351 | 126.392 | 257.611 | 264.777 |
| 704.871 | 627.420 | 330.794 | 121.406 | 162.073 | 288.382 |

Means

$$
\begin{array}{llllll}
950.8210 & 959.8047 & 419.9355 & 350.0 .090 & 250.6422 & 159.9830
\end{array}
$$

Standard deviations

$$
\begin{array}{llllll}
470.8245 & 384.0735 & 162.1550 & 165.4883 & 88.0898 & 142.6572
\end{array}
$$

Skewness co-efficient

$$
\begin{array}{llllll}
-0.1992 & -0.2267 & 0.2002 & 0.1673 & 0.1021 & 0.4554
\end{array}
$$

slopes
$-0.2855$
0.5034
0.1178
0.1136
0.0350
-0. 0.5241

Correlations with previous month
$-0.1378$
0.6171
0.2789
0.1113
0.0657
$-0.3237$


FIG. 5 MEAN MONTHLY INFLOWS OF THREE LOCATIONS


FIG. 6 CORRELATION WITH PREVIOUS MONTH LOCATION ONE


FIG. 7 CORRELATION WITH PREVIOUS MONH - :IOCATION TWO)


FIG. 8 CORRELATION WITH PREVIOUS MONTH - $\underset{\text { LHREE }}{\text { LOCATION }}$

Table 8. Comparison of measure and generated statistics - Thomas Fiering Model Generated sample size 100 years

## Location 1

| Months | Measured Flow Statistics |  |  | Generated Flow Statistics |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mu$ | $\sigma$ | $\checkmark$ | $\mu$ | $\sigma$ | $\checkmark$ |
| January | 8.1 | 6.3 | -0.01 | 7.1664 | 5.1702 | 0.9147 |
| February | 5.8 | 4.9 | 0.8 | 5.3633 | 3.9439 | 0.9699 |
| March | 4.6 | 4.3 | 0.5 | 4.4477 | 3.3696 | 0.9034 |
| April | 3.6 | 3.8 | 0.4 | 3.6149 | 2.9244 | 0.8066 |
| May | 6.3 | 6.9 | 0.6 | 6.1955 | 5.6544 | 0.8891 |
| June | 19.1 | 13.5 | 0.2 | 16.2151 | 1.0.9549 | 0.4198 |
| July | 46.8 | 25.9 | 0.5 | 42.032 | 23.6905 | 0.6178 |
| August | 66.8 | 32.8 | 0.1 | 55.309 | 31.1307 | 0.6368 |
| September | 34.2 | 16.2 | 0.9 | 29.567 | 16.55 .85 | 0.5123 |
| October | 26.3 | 12.7 | 0.9 | 25.235 | 12.503 | 0.5640 |
| November | 22.1 | 16.8 | 0.5 | 23.579 | 14.422 | 0.3843 |
| December | 10.3 | 5.6 | 0.9 | 10.785 | 5.54 | 0.4511 |

Table 9. Comparison of measured and generated statistics - Thomas Fiering Model Generated sample size - 100 years

## Location 2

| Months | Measured Flow Statistics |  |  | Generated Flow Statistics |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | M | $\underline{\sigma}$ | $\checkmark$ | $\mu$ | $\sigma$ | $V$ |
| January | 11.96 | 3.63 | 0.41 | 9.21 | 6.728 | 0.5169 |
| February | 7.90 | 7.36 | 0.98 | 6.1587 | 5.158 | 0.0694 |
| March | 7.35 | 7.32 | 0.99 | 5.289 | 4.997 | 0.9873 |
| April | 9.07 | 7.32 | 0.76 | 6.79 | 5.745 | 0.8142 |
| May | 19.06 | 11.71 | 0.55 | 14.0978 | 12.085 | 0.6667 |
| June | 84.37 | 75.18 | 0.50 | 93.592 | 65.946 | 0.2082 |
| July | 215.65 | 88.67 | -0.07 | 219.585 | 95.7561 | 0.1013 |
| August | 186.03 | 112.15 | 0.54 | 205.549 | 144.588 | 0.5165 |
| September | 75.39 | 37.20 | 0.60 | 81.282 | 46.897 | 0.6544 |
| October | 69.38 | 33.87 | 0.74 | 67.481 | 29.942 | 0.5574 |
| November | 71.37 | 85.03 | -0.07 | 79.072 | 64.931 | 0.0622 |
| December | 20.28 | 10.31 | 0.27 | 18.0357 | 15.64 | 0.2198 |

Tablel0. Comparison of measured and.generated staミistics - Thomas Fiering model Generated sample size : 100 years

Location 3

| Months | Measured Flow Statistics |  |  | Generated Flow Statistics |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | A | $\sigma$ | $V$ | fr | $\sigma$ | $\gamma$ |
| January | 43.1 | 13.5 | 0.23 | 39.647 | 13.703 | 0.1245 |
| February | 23.6 | 10.6 | 0.92 | 22.683 | 16.514 | 0.8849 |
| March | 16.5 | 9.5 | 0.95 | 15.426 | 7.810 | 0.9342 |
| April | 17.3 | 13.0 | 0.96 | 15.048 | 10.306 | 0.9539 |
| May | 47.9 | 36.2 | 0.71 | 41.270 | 32.367 | 0.5997 |
| June | 366.5 | 292.6 | -0.02 | 314.034 | ?27.236 | 0.0042 |
| July | 1012.5 | 401.7 | -0.187 | 950.821 | 170.824 | 0.1378 |
| August | 938.9 | 396.4 | 0.387 | 959.804 | 384.735 | 0.1710 |
| September | 392.8 | 134.8 | 0.217 | 419.935 | 162.155 | 0.2799 |
| October | 331.2 | 153.7 | 0.441 | 350.009 | . 65.488 | 0.1113 |
| November | 216.5 | 98.9 | 0.073 | 250.642 | 88.089 | 0.0657 |
| December | 140.1 | 197.4 | -0.26 | 159.983 | 142.657 | 0.3837 |



Fig. 9 PROBABILITY CHART FOR THE MONTH OF MAY AT LOCATION ONE


Fig... 10 PROBABIIITY CHART FOR THE MONTH OF JUNE AT LCCATION ONE.


Fig. 11 probabillity chart for the month of july at location one.


Fig. 12 PROBABILITY CHART FOR THE MONTH OF AUGUST AT LOCATION ONE


Fig. 13 PROBABILITY CHART FOR THE MONTH OF SEPTEMBER AT LOCATION THO



Fig. 15 PROBABILITY CHART FOR THE MONTH OF NOVEMBER AT LOCATION TWO


Fig. 16 PROBABILITY CHART FOR THE MONTH OF DECEMBER AT LOCATION TWO


Fig. 17. PROBABILITY CHART FOR THE MONTH OF JANUARY AT LOCATION THREE


Fig. 18 probability chart for the month of february at location three


Fig. 19. PROBABILITY CHART FOR THE MONTH OF MARCH AT LOCATION THREE


Fig. $\because 20$ PROBABILITY CHART FOR THE MONTH OF APRIL AT LOCATION ThKEE


EIG. 21 TIME SERIES PLOT - LOCATION ONE


FIG.22. STANDARD DEVIATIONS OF HISTORIC AND GENERATED FLOW at location one


FIG. 23. STANDARD DEVIATIONS OF HISTORIC AND GENERATED FLOW at location two


FIG. 24 STANDARD DEVIATIONS OF HISTORIC AND GENERATED FLOW AT LOCATION THREE

### 4.2 Statistical analysis

The monthly streamflow data has been checked for its consistency with normal distribution. The ranges of values for location two are shown in Table 4. It is seen that the streamflows are mostly consistent with normal distribution. The mean monthly inflows to the three locations are plotted in Fig. 5. The statistical analysis shows that flows generated by the model agree with the trend of historic flows.

Weibull's method is used for the frequency analysis of the monthly streamflow data. Using the tabulated values of the probability, probability curves have been drawn for all the months. Probability curves for various months forlacations one, two and three are shown in fig. 9 to 20.

The statistical analysis of annual flows has been done and the values of annual mean, standard deviation and coefficient of correlation are shown in Table 8,9 \& 10.The 75 per cent probable annual flows are 133.2 , 508.4 and $4210 \mathrm{Mm}^{3}$ for location one, two, three respectively. An annual time series plot of the inflows has been made and compared with five year moving average. Figure.21. shows the total annual flows and five years moving average for location two. From the data it is seen that June to October the rivers cariry the maximum inflows due to the two monsoons.

The model verification tests reveals that Thomas Fiering model holds good for the site selected. The statistical analysis also ensures the suitability of the model for the site. So the model preserve the statistical parameters like mean, standard deviation and coefficient of correlation. This points out that the simulation model is very effective in the management of water resources systems.

The scarcity of water and conflicts among purposes causes the problem of reservoir operation. There is virtually no serious management problem, if plenty of water is available. So an optimisation approach is needed, for the sptimal utilisation of available resources.

Here a suitable computer simulation model is developed using the available streamflow data. From the model verification tests it was observed that the Thomas Fiering model holds good for the site selected. Hence data is generated for a period of hundred years. The statistical corvarison of the synthetic data and the historical data assures that the generated data can be treated as equal to the historical data.

The comparison of statistical parameters of historical and generated data includes the comparison of mean, standard deviation and coefficient of correlation computed from generated data with the actual value of those statistics computed from the historical data. From the Table 8-10 which compares the various statistical parameters of both historical and generated flows, it can be seen that the model chosen very much holds good. The mean monthly flow of $21.15 \mathrm{Mm}^{3}$ obtained from observed data of location 1 compares favourably with the
monthly mean of $18.01 \mathrm{Mm}^{3}$ obtained from generated streamflow data. The values of standard deviation of historic data shows good agreement with the corresponding parameter per synthetic data.

There is good agreement between the flow duration curves of both observed and synthesised data for all the months. As far as the preservation of the historical statistics is concerned, the coefficient of skewness was also well preserved.

The simulation model could preserve the mean, the standard deviation and the correlation coefficient. However, the performance of the stochastic model is to be evaluated by applying the different generated sequences obtained using the model in the water resources system under consideration.

The study on computer simulation shows that the model developed is an effective tool for the reservoir systems proper management.


## REFERENCES

Askew, A.J. et al. 1971. A comparative study of critical drought simulation. Water Resources Res. 1: 52-62.

Benson, M.A. and Matalas, N.C. 1967. Synthetic hydrology based on regional statistical parameters. Water Resources Res. 3 (4).

Centre for Water Resources Development and Management. 1987. Rainfall Run-off Criteria for the Chaliyar Basin of Western Ghat Region, Final Report, Research Scheme applied to River Valley Projects, Kozhikode.

Clarke, R.T. 1913. Mathematical Models in Hydrology, Food and Agricultural Organization, Irrigation and Drainage Paper.

Duggal, K.N. and Khepar, S.O. 1981. A linear programming model to conjuctive use of surface water and groundwater. J. Institution of Engineers (India). 61.

Fiering, M.B. 1967. Stheamblow Synthesis, Harvest University Press, Cambridge, Mass.

Gerals, F.A. 1978. Generation of ungauged streamflow data, Proc. ASCE, J. Hydraulic Division 104 (2): 377-384.

Huschmidt, H.M. 1966. Simulation Techniques for Design of Water Resources Systems. Harward University Press, Cambridge.

Jackson. 1976. Use of streamflow models in Planning. Water Resources Res. 11 (1): 54-63.

Jose, D. Salas. 1992. Synthetic disaggregation scheme for synthetic hydrology. J. Hydraulic Engg., American Society of Civil Engineers 18 (5).

Matalas, N.C. 1987. Mathematical assessment of synthetic hydrology. Water Resources Res. 3(4): 937-946.

Mcmohan, T.A. and Miller, A.J. 1971. Application of the Thomas Fiering model to skewed hydrologic data. Water Resources Res. 7(5): 1338-1340.

Mobasheri, T. and Hasfoe, R. 1970. A two stage optimisation model for design of a multi-purpose reservoir. Water Resources Res. 6 (1).

Mort.en Rango, 1985. Improvement of the updating routine in the Mike II modelling system for real time flood forecasting, IIHR Report 1 (325).

Padmacharan Naik. 1990. Stochastic Modelling of streamflow, M.Tech. thesis, I.I.T., Madras.

Paul Jobi, v. 1989. Op̈imisation of multipurpose multireservoir systems, Ph.D. thesis, Hydraulic and Water Resources Engineering Division, IIT, Madras.
*Ranga, K. and Narasimhamurthy, K.V. 1990. Synthetic stremflow wing time series analysis.

RaO, S.B. 1987. Optimal Reservoir Operation Using Linear Programming and Goal Programming, M.Tech. thesis, IIT, Madras.

Seth, S.M.et al. 1985. Application of Thomas Fiering Model for Monthly Streamflow Generation in Chaliyar River Basin. National Institute of Hydrology, Report CS-8, Roorkee.

Srivastava, D.K. and. Tiwari, V.R. 1978. Optimisation for Optimal Allocation of Narmada Waters, Central Board of Irrigation and Power 1 (l).

Shih, Suan Fu. 1976. Analyse of Synthetic Streamflow Sequences, Int. Symposium on Hydrologic Characteristics on N'ver Basins, Japan.

Walesh, G. 1974. Simulation in watershed planning. J. Hydraulic Division 99 (9).

Appendices

## PROGRAK LISTING FOR UNIYARIATE THOTAS FIERIMG MODEL FON <br> STREAMFLON GENERATION

```
`
C UNIVARJATE THOMAG'FIERIMG MODEL FOR GENERATION OF STREAMFLOK
C
        COMMON B(12), R(12)
        DJMENSION Q(480), H(480), RES(480), T!TLE(88),SYNQ(1288),E(1288),
        IMONS(12), AVEMON(12), SDMON(121,GAVEMON(12'),GSDHON(12), DAVEMOK(12)
        1,DSUHON(12)
C Q IS thE INPUT SERIES OF flOMS, NE IS thE hORKING transfORMATION
C DF Q, mONS HOLOS THE MONTH BY TITLE
C RFS IS THE RESIDUAL FROM THE FIT
C B AND R ARE THE SLOPES OF REGRESSION AND CORRESLATION COEFFICIENT
C AVEMDN, SDMON ARE MONTHLY MEANS AND STANDARD DEYIATIONS.
C SYNQ AND E ARE GENERATED SERIES AND GENERATED RESIDUALS FOR 100 YR
C INPUT SECTIDN
        WRITE(16,444)
CA44 FORMAT(5X,'gENERATED FLOHS USING THOMAS FIERING MODEL HITH LOG NOR
C IMAL'TRANSFORMATION'//)
444 FORMAT(5x,'gENERATED'FLOHS USING THOMAS FIERING MODEL. HITH SQUARE
        IRODT TRANSFORMATION'///
        NYEARS=14
C READ (12,2)NYEARS
2 FORMAT(14)
        HFITE(18:1800)NYEARS
180日 FORMAT(15X,'NO. OF YEARS DATA='.!3/)
        *RITE(16,300)
300 FORMAT(1X,119('''')/6X,'JUN',5X,'JUL'/6X,'AUG',7X,'GEP',6X,'OCT',6X
    1,'NOV',5X,'DEC',5X,'JAN',6X,'FEB',7X,'MAR',7X,'APR',GX,'MAY',IX,I1
    29('I'))
        N=NYEARS:12
        NA=N-1
        READ(12,183)(Q(1),101,N)
103 FORMAT(7X10.3/5F18.3)
        WRITE(16,185)(Q(1),1=1,N)
105 FORMAT(5X,' &tttwt% FLONS titf!'/(12FG.1)
        CALL EXAM(Q,NYEARS,DAVEMON,DGDMON)
        DO 979 lx1
C Q(1)=ALOG(Q(1))
        Q(I)=SQRT(0(1))
999 CONTINUE
    WRITE(16,306)
    HRITE(It,65t) (0(I),I=1,N)
66n FORMAT(5x,'gQUARE ROOT VALUES OF ACTUAL FLOWS':il:'12F
    GALL EXAM(Q,NYEARS,DAVEHON, DSDMON)
    DO 303 !=1,12
    AVEMON(I)=DAVEMON(I)
303 SDMOH(I)=DSDMON(1)
```

```
        00 7 ! = 1.N
        l=MOD(1,12)
        IF(J.EO.0) J=12
        WO(1)=Q(1)-AVEMON(J)
        DO 8 i=2,N
        j=1-1
        K=MOD{1,12)
        A=B(K)$HQ(J)
        RES(J)=WO\I)-A
    8 CONTINUE
        HRITE(16,109)(RES(1), I=1,NA)
    109 FORMAT('RESIDUALS DF FIT'/9X,11F9.1/(12F9.1))
C EXAKIME RESIDUALS
    CALL BASIC(RES,AVER,SD,NA)
    HRITE(16,110)AVER,SD
    110 FORMAT(//'MEAN OF RESIDUALS IS =', 2%,FG, S,EX:'AND VARIANCE= 1S',3X
        1,F9.3)
        CALL RANDOK(E,1208)
        DO 10 I=1,12
        CORER(1)
    10 TITLE(1)=SDMON(1)&SGRT(1.0-COR&CȮR)
        SYNQ(1) cB(1)*&(N)+E(1):TITLE(I)
        DO N9 I=2,1200
        J_1-1
        K=MOD(1,12)
        IF (K,EQ, B)K=12
    9 SYMQ(I)=R(K)tSYNQ(J) +E(I)ITITLE(K)
C MONTHLY MEANS
        DO 31 I=1,1208
        J=MOD(1,12)
        IF(J,EQ,8)J=12
    03! SYNQ(I) =EXP(SYNQ(I) +AVEMON(J))
    31 SYNQ(I) =(SYHO(I) + AVEMON(0)):$2
C EXAMINE GENERATED DATA
        HRITE(16,380)
        HRITE(16,106)(SYMO(1),I=1,1200).
        CALL EXAM(SYMG,18Q, GAYEMON, ESDMON)
```



```
        1(12F9*.2))
        STOF
        END
        SURROUTINE RANDOM{E,H)
        DIMENSION E{N)
        1XE187374;823
        00 20 1=1,N
        CALI GAUSS (IX,1:8,8.,V)
    20 E(I)=V
    RETURN
    END
    SURROUTINE EXAM(Q,NYEARS,AVEMON,SDMON)
C A SUBROUTJNE TỌ CALCULATE MNNTHLY HEANS: SD.SLOFES & CORRELATIOHS
    COMMON B(12), P(12)
    DIMENSION Q(1),WORKI(108), HORKJ(188),AVEHON(12),SDMON(12)
    H=NYEARS:12
    DO 20 1=12,N,12
```

    HORK:1(J)=0(1)
    CALL BASIC(HORH:1, AVEMON(12), SDMON(12),'NYEARS)
    0021 I=1,12
    M=1-1
    IF(M.EQ.O)M=12
    0022 J=1,N,12
    K={J+11)/12
    22 HORKJ(K) \#G(J)
CALL BASIC(HORKJ,AVEKON(I),SDMON(I),NYEARS)
1F(1-1) 24,25,24
25 HYEARS=NYEARS-1
A=WORK$1)
    DO 26 1J=1,NYEARS
    26 HORKJ(IJ)=WORK\\IJ+1)
    24 CALL BORREL(HORKI,HORKJ,AVEMEIS(K),AVEMON(I),SDMON(M),SDMON(I), B(I)
    1,R(I),NYEAFS)
    IF(1-1)27,28,27
    28 NYEARS=NYEARS +1
    MN=HYEARS-1
    DO 20 IJxI,NN
    IK工NYEARS-IJ
    29 HORKJ (IK)=NORKJ (IK-1)
    HORKJ(1)=A
    27 DO 23 K=1,NYEARS
    25 HORKI(K)=WORKJ(K)
    2: CONTINUE
C OUTPUT INFORMATIQN FOR CHECK:IMG
    HRITE (16,186) AVEMOH
    WRITE(16,114)SDMON
    WRITE(16,107)B
    WRITE(16,115)R
    10b FORMAT (4X,'MEANS'/12F9.21
    114 FORMAT(4X,'STANDARD DEVIATIONS'///12F9.2)
    107 FORMAT (//'SLOPES'///L2F I2.4)
    115 FORMAT(//'CORRELATIONS HITH PREVIOUS MONTH'//12F9.3)
        RETURN
        END
        SUBROUTINE BASIC(X,AVER,SD,H)
        DIMENSION X(I)
        SX=0.8
        SSX=0.0
        RN=1.8/FLOAT(N)
        OO&l=!,N,1
        A= X(I)
        SX=SX+A
        AVER=SX:RN
        DO 2 I=1,N
        A=X(I)
2 SSX=SSX+(A-AVER) ((A-AVER)
    SD=SQRT(SSX/FLOAT{N-1)\
    KETURN
    END
    SURROUTIAE EORREL(X,Y, XMEAN, YMEAN,SDK,SDY,SLOPE,R,N)
    DIMENSION K(1),Y(1), WX\100),WY(100)
```
    \(\mathrm{J}=\mathrm{j}, 12$

$$
\begin{aligned}
& \text { Le } 1 \quad i=1 . N \\
& \text { WX: } 1 \mathrm{I}=\mathrm{X}(1)-X M E A N \\
& \text { WY(1) =Y(1)-YMEAR } \\
& 55 x=0.0 \\
& 5 S Y=0.0 \\
& 0021=1, N \\
& A=W \times(1) \\
& B=\mathrm{AY} \text { (I) } \\
& S X Y=S X Y+A+B \\
& S S X=S S X+A t E \\
& 2 \text { SSYESSY+EKB } \\
& \text { SSX=SQRT(SSX) } \\
& R=S X Y /(S S X \$ S S Y) \\
& \text { SLOPE=RISSY/SSX } \\
& \text { GETURN }
\end{aligned}
$$

# SYNTHETIC GENERATION OF STREAMFLOW DATA USING COMPUTER SIMULATION MODEL 

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Levan $\mathcal{K} \cdot \mathcal{V}$.

## ABSTRACT OF A THESIS

Submitted in Partial fulfilment of the requirement for the degree

# MASTER OF TECHNOLOGY IN AGRICULTURAL ENGINEERING Faculty of Rgricultural Enginecring <br> Kerala Agricultural Clniversity 

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## ABSTRACT

A greater emphasis has to be laid in the planned optimum utilisation of the available water resources due to the increasing demand for agricultural, domestic and industrial purposes. Though the country has been favoured with plentiful rainfall, the spatial and temporal distribution is quite uneven and erratic resullting in droughts and floods in several parts of the country. Kerala experiences severe shortage of water for dormestic, irrigation and hydropower generation during the, summer months. The need for an assured supply of water, for the summer months has become highly essential for, the state. Therefore the present need of the state is the scientific approach in water resources planning to achíeve optimum use and conservation of available water besources. Considering this an effort/ has been made to ievelop a computer simulation model for the synthetic feneration of streamflow data for Chaliyar, one of the larger basins of region the starí

The streamflow-data (15) needed for various purposes as far as the water resources system is concerned. However, the available data for the required duration is-inadequate. So we lave to generate synthetic, dáta.


#### Abstract

were The data was collected from different river gauging stations for different durations. A suitable mathematical model namely Thomas Fiering Model was developed for the generation of synthetic data. The model was fitted for the observed monthly streamflows. The validity of the model was checked by comparing the statistical parameters of historical and generated data and by comparing the flow duration curves.


It is seen that the model preserves various statistical parameters like mean, standard deviation and correlation coefficient. The study reveals that the computer simulation model developed is a very effective tool in the Drover management of water resources system.

