STOCHASTIC STREAMFLOW GENERATION USING DAILY RAINFALL DATA

A DISSERTATION
Submitted in Partial fulfilment of the requirements for the award of the degree
of
MASTER OF ENGINEERING
in
HYDROLOGY

By
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C E R T I F I C A T E

Certified that the dissertation entitled 'STOCHASTIC STREAMFLOW GENERATION USING DAILY RAINFALL DATA' which is being submitted by Mr. J.T.B. Obeysekera in partial fulfilment of the requirements for the award of the degree of Master of Engineering in Hydrology of the University of Roorkee, Roorkee, is a record of the candidate's own bonafide work carried out by him under my supervision and guidance. To the best of my knowledge the matter embodied in this dissertation has not been submitted for the award of any other degree or diploma.

This is further to certify that Mr. J.T.B. Obeysekera has worked for a period of six months from Ist October 1977 to 31st March 1978 in the preparation of this dissertation under my guidance, at this University.

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DATED: April, 1978 J. T. B. OBEYSEKERA

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S Y N O P S I S

The adequate development of water resources requires the use of planning techniques which depend to a large extent on reliable estimates of the key hydrologic variables. One of the most important of these is the streamflow at the point of interest of the river. The information that is required very often are the quantity and availability and the frequency of occurance of floods and droughts. Although many streams have been gauged to provide continuous streamflow records, very often planners and designers face with little or no available streamflow information. Many investigators have developed techniques for synthetic generation of streamflow sequences using the available data of streamflow. For areas with inadequate streamflow data, techniques have been developed, which syntheize the sequences of rainfall data and use such generated sequences to obtain streamflow sequences using suitable rainfall-runoff relationships or conceptual models. Such a technique which combines ' synthesis' and 'simulation' enables synthetic generation of number of data samples of periods longer than that of historical data for better design of projects by providing possible patterns of extreme cases.

Very often the available data consist of very short record of streamflow, say five to six years. The present study has been devoted to evolve a stochastic daily streamflow model using very limited data of rainfall and runoff and also to examine the performance of the approach in such a case of limited data.

The proposed stochastic daily streamflow model used for the present study consists of two seperate models; a stochastic multi-station daily rainfall generator developed on the lines suggested by Kraeger (1971) and a deterministic daily rainfall-runoff model developed on the basis of division of the catchment in to subareas using isochrones and using travel coefficients to account for the natural transformation of discharge along the length of the river. The stochastic multi-station rainfall generator consists of a Markov model, representing the probability of a wet day following a wet day or of a dry day following a dry day, to determine whether a rainfall station will or will not receive precipitation. If a wet day is generated, the amount of rainfall is determined by either sampling from a cumulative distribution of the historic daily rainfall amounts or by sampling from a regression equation that relates rainfall occuring the same day at adjacent stations.

The daily rainfall-runoff model requires determination of lag time, division of catchment into subareas by means of isochrones, and the travel coefficients for individual subareas. The travel coefficients account for the natural transformation of the discharge hydrograph during the process of movement along the length of the river system. The parameters of the model i.e. initial travel coefficients, basin travel time etc. are determined through several calibration trials by a computer model. The final parameters obtained are then used to transform generated daily rainfall to daily streamflow.

The proposed model has been applied to Naula catchment of Ramganga basin for which only six years of daily rainfall data are available. The stochastic daily rainfall model gives satisfactory results in reproducing statistics (mean and standard deviation) of observed sequence, in spite of the limited data being used. The daily rainfall runoff model adequately simulates the observed direct runoff hydrographs for the monsoon season and when it is used with rainfall generator the statistics of generated daily direct runoff sequences compare favourably well with those of observed. The performance of proposed approach using limited data is quite encouraging and further work should be done in this direction using data for other catchments.

CHAPTER-1

INTRODUCTION

1.1. NEED OF ' STOCHASTIC STREAMFLOW RECORDS'

In a hydrologic design the designer usually wishes to see how the particular water-control facility will perform for representative future hydrologic inputs. The designer is not in a position to know what future flows or future precipitation events will be, but he can assume that future events will have the same stochastic properties as the observed historical data. It is this assumption that forms the basis for generation of equiprobable input traces, each trace having similar statistical properties. Each input sequence yields a sequence of outputs from the system under investigation. By determining system response to such a set of new hydrologic sequences one may extract probabilistic information about the performance of the system which would be useful for design and decision making.

The complexity of water resource systems is such that the problems arising in their design and control, with few exceptions, defy solution by classical methods of mathematics and statistics. Since the advent of the digital computer, however, these problems have been susceptible to study by the use of simulation techniques. The problem of reproducing mathematically the characteristics observed in a series of natural phenomena has therefore received considerable attention, and in recent years the literature has abounded with papers devoted to synthesis of various hydrologic data series.

The use of models to represent, simulate and generate the annual and monthly sequences is already widespread in hydrology. The generated sequences have been found to reproduce adequately the historic statistics. In many situations, when a large scale project is involved, further refinement of the time scale becomes essential. Beard (1968) stated that ' although fluctuations of flows within a month usually have minor influence on storage required for conservation purposes, such fluctuations are ordinarily crucial in the determination of reservoir space requirements for flood control'. The optimization of a system involving a run-off-the-river hydroelectric power plant is another example, where lesser period say weekly or daily data are needed.

1.2. STOCHASTIC ANALYSIS OF PRECIPITATION

If relatively long, undisturbed, observed streamflow records were available, the assumption that the observed streamflow statistics are equal to the true population statistics would be valid. More often, because of continual watershed development and short streamflow records, observed streamflow data are not representative of present stream and watershed conditions. Caliberation of a model with unrepresentative data results in inaccurately derived parameter values and thus limits their transferability and the utility of the model for synthesizing records. Thus stochastic streamflow data has little value if the statistics used in the generation model are unrepresentative of the present watershed regime.

If streamflow records are not available or inadequate for the synthesis of stochastic streamflow record, the next available source of hydrologic information is precipitation data. Precipitation records constitute the largest data base and hence any model developed to use precipitation as the primary input would have the widest application. Precipitation records are generally unaffected by watershed developments and hence they can be reliably used in stochastic models. Furthermore, the parameters derived from precipitation records are more stable on account of the longer sequences generally available, as compared to streamflow data.

The generated rainfall samples can be used in deterministic models which route rainfall through several phases of the land segment of the hydrologic cycle. These models implicitly assume that the stochasticity of the streamflow process is due only to rainfall. These models may be used to predict modifications in the streamflow due to changes in the watershed (for example, the urbanization) without modifying the generation model for precipitation.

1.3. OBJECTIVES OF THE STUDY

This study is devoted to a development of a model for generation of synthetic daily streamflow through stochastic generation of daily rainfall using limited data.

The stochastic streamflow model is comprised of two separate models -

1) A stochastic multi-station daily rainfall generator on lines of the methodology developed by Kraeger(1971).

2) A deterministic daily rainfall-runoff model based on isochrones and travel coefficients.

The multi-station rainfall generation is further divided into two functions. The first step determines whether a rainfall station will or will not receive precipitation and if precipitation is indicated, the second step determines the amount of rainfall. The first step is essentially a Markov model representing the probability of a wet day following a wet day or of a dry day following a dry day. If a wet day is generated, the amount of rainfall is determined in the second step by either sampling from a cumulative distribution of the historic daily rainfall amounts or by sampling from a regression equation that relates rainfall occuring on the same day at adjacent stations. Through these two steps, the statistics of storm duration, inter-storm period lengths and daily rainfall amounts can be adequately reproduced.

The deterministic daily rainfall-runoff model requires the catchment to be divided into subareas on the basis of isochrones and the determination of appropriate travel coefficients for the subareas through an optimization procedure. The travel coefficients accomplish the natural transformation of the discharge hydrograph during the process of movement along the length of the river system from the upper sections to the lower outlet.

1.4. APPLICATION OF THE PROPOSED MODEL TO A NATURAL CATCHMENT

One of the main objectives of the present study was to investigate the feasibility of developing the proposed model using limited data, say ten years or less. For this purpose the Naula catchment of Ramganga basin in Uttar Pradesh of India was chosen and the available rainfall-runoff record of six years length was used. Data comprised of daily rainfall values at six rain gauge stations inside the catchment and daily run-off values at Naula gauge site.

1.5. OUTLINE OF CHAPTER CONTENTS

Chapter 2 gives a brief survey on the previous studies of hydrologic modelling related to simulation, forecasting, data generation etc.

Chapter 3 presents the theory on which the model is based and the methodology proposed for the present study. The study consists of development of two models to yield a single stochastic daily streamflow model. The first model generates stochastic daily rainfall whereas the second transforms the rainfall data into daily runoff. In this chapter the conceptual framework for each of the model has been developed.

In Chapter 4 both the developed models have been caliberated with the help of daily rainfall and runoff data of Ramganga river upto Naula gauge site. Intermediate results of both the models have been given in tabular form. The models have been tested to investigate the reproduction of major statistics of observed data in various lengths of generated data.

Chapter 5 presents discussions of results obtained by both the models and recommendations for further studies.

CHAPTER-2

A BRIEF REVIEW OF LITERATURE ON MODELS FOR RAINFALL AND RUNOFF

2.1. INTRODUCTION

Several research papers have been published on modelling of rainfall and runoff processes. No attempt is made to report about all the efforts and contributions on this subject but only those that are relevant to the present study. For the present study the survey of literature was carried out on the following related aspects.

1. Models for synthetic streamflow generation
2. Models for synthesis of rainfall data
3. Rainfall runoff relations.

The discussion of literature on the above aspects has been given in the following sections of this Chapter.

2.2. REVIEW OF RECENT WORK ON MODELS FOR SYNTHETIC GENERATION OF STREAMFLOW

Fiering (1967) reported that an annual stochastic streamflow model, assuming independence between years, can consists of a cumulative normal distribution with the mean and variance of the observed historic record. Sampling randomly from the cumulative distribution using uniformly distributed random variates, a sequence of annual streamflow volumes that will have the statistics of the observed data will be produced. He presented a model for seasonal or monthly streamflow also but in this model it was not possible to treat the seasons or months following one another as independent random variables.

In order to maintain the correlation between periods in the generation of streamflow data, a recursive relationship was developed between the periods.

This model assumes that the streamflow is a normally distributed random variable. In areas where the mean period streamflow is high with a small variance, an assumption of normally distributed streamflow may be adequate. With a high coefficient of variation, use of a normal distribution may produce many negative streamflow values and generate a meaningless streamflow record.

In an effort to develop a generation procedure that would maintain the period statistics and eliminate negative streamflows, Beard (1962) proposed a logarithmic transformation of the streamflow data. The logarithms of the streamflows are assumed normally distributed and the generation procedure is similar to that of Fiering. A Skew coefficient may be used to provide for a better fit of generated data to historic data.

In 1966, Roesner and Yevjevich presented a paper describing the mathematical model for monthly streamflow. In this paper the problems of time series stationarity, its periodicity and the use of techniques of serial correlation and variance spectrum in the analysis of time series structures were reviewed and summarized.

Similar procedure was applied to daily streamflow sequence by Quimpo (1967). In his study the daily runoff records of 17 rivers were used and it was found that all the residual series satisfied the second order autoregressive representation.

Kottegoda (1972) avoided the complexities of daily streamflow because, ' the high variance of the flows, the unconventional probability distributions, and the failure of the simulation processes to transfer hydrograph characteristics of the historical flows '. Instead he aimed to model the 5-day streamflow.

Since the direct approach for generating daily sequences is unsuccessful most of the time, one alternative procedure is often used, namely the values are generated for longer time intervals, say a month or a week, and then distributed among the days. Green (1973) used Kottegoda's model to generate sequences of 5-day average flows, and then split them into daily average flows using a sophisticated method of interpolation. A stochastic error term is superimposed on the interpolated daily flows, which represents the non-deterministic component of daily time series.

Kottegoda and Yevjevich(1977) compared four types of stochastic two station models for the generation of samples of hydrologic runoff series by generating new samples of five pairs of station annual runoff series. The models tested were those of Fiering, Lawrance, Yevjenich and Matalas and it was found that all four models gave basically similar results.

To determine how well a given model fits, any streamflow record requires adequate data. Where there is insufficient streamflow data, these models cannot be used with reliability. Even 50 odd years may not be sufficient to define the population statistics for long term storage studies. On the other hand the precipitation records are longer than streamflow records and hence the parameters are more stable. Therefore in an attempt to accomplish stochastic streamflow generation in areas where the streamflow data is poor, stochastic generation of rainfall which would then be transformed into streamflow values appears to be a logical approach.

The present study is concerned with the generation of stochastic daily streamflow records. As far as the direct synthesis of daily streamflow records is considered very little evidence is found in literature. This is mainly due to several difficulties encountered in the attempts made to develop models for synthesis of daily streamflow. For example Tao(1973) found that no distribution was found to fit the frequency distribution of the daily streamflow, because of the sharp peak and high skewness of the empirical distributions. However for longer time intervals he was able to fit distribution with unusually high number of parameters. Kottegoda (1972) also observed similar difficulties as described above. These difficulties of generating daily streamflow directly, have made the researchers in this field to go for models for generation of daily rainfall amounts which inturn may be transformed into daily streamflow by a suitable rainfall-runoff model.

2.3. REVIEW OF WORK ON SYNTHESIS OF RAINFALL DATA

The probability of a wet day appears to have been first studied by Newham (1916), who concluded that in England, wet and dry weather is persistent and that the probability of a wet day is related to the number of preceeding wet days. This was later confirmed by Lawrence (1954) who showed in addition that the likelihood of dry weather persisting decreased as the length of the dry period increased.

By contrast Longley (1953) showed that in Canada the probability of a dry day following another dry day is almost independent of the number of preceeding dry days. He also found the same relationship for wet days.

The first mathematical model to describe rainy and non rainy days was compiled in 1957 by Gabriel and Neumann(1962) using data from Isreal. They found that persistence existed only between sucessive daily rainfalls and obtained a good fit of the observed data using a first order Markov chain model.

For intervals of less than a day the persistence within storms makes the stochastic modelling of rainfall rather complex. Chow and Ramaseshan (1965) presented a method to generate hourly values of rainfall and it was of the form

$$P_t = r P_{t-1} + e$$

Where e has a distribution that varies through the storm and is constrained so that P_t is non negative.

Pattison (1964) developed a method for the generation of hourly rainfall at one station. He divided the year into periods, assuming each period to have a uniform probability of rainfall. The historic hourly rainfall for each period is analyzed to develop transition probabilities of a wet hour following a wet hour and a dry hour following a dry hour. These transition probabilities were further divided into levels to represent the probability of a wet hour following another wet hour during which a given amount of rainfall occurs. Rainfall amounts were generated by sampling randomly from the historic hourly rainfall and by linear regression relationships developed between successive hours of rainfall.

Grace and Eagleson (1966) examined rainfall on a ten-minute time interval. Studying only summer storms, distributions were fitted to the observed interstorm periods and storm durations. A linear regression relationship was developed relating storm amount to storm duration. The procedure was to randomly choose an interstorm period and then randomly choose a storm duration. With the storm duration as the independent variable in the linear regression equation, a storm rainfall amount was calculated. Subdivision within storms was achieved via an urn model giving short term persistence.

Raudkivi and Lawgun (1974) also presented a stochastic model for generation of rainfall sequences based on 10 minute time units. It included the use of dependendent time series and a random component that is non normally distributed. The model was applied successfully to three climatically different regions.

Wilkinson and Tavares (1972) proposed a methodology for the synthesis of spatially distributed short time increment storm sequences. In this method, instead of using a sequential generation procedure with fixed time increments, the storm duration is itself used as a random variable with the hyetograph shapes being generated subsequently.

Cole and Sherriff (1972) proposed single and multisite models for the synthesis of rainfall records. Daily rainfall at one site is synthesized in two stages, first by random selection of duration of alternating wet and dry spells and secondly by a Markov chain of daily rainfall amounts within each wet spell. Extension of the single site sequence to other sites may be tackled by sampling from historical patterns but is more elegantly achieved by multivariate versions of the Markov chain.

Kraeger (1971) proposed a methodology to generate synthetic sequences of daily rainfall at more than one station in a network of related stations. In this method transition probability matrices and the linear regression relationships among the stations were developed and subsequently used for the sequential generation of rainfall. The amount of rain at the first station, if a wet day occurs, would be sampled from the cumulative distribution of the same. The occurance of wet days at individual stations would be decided on the basis of transition probabilities and the amounts of rainfall at the following stations would be computed by the regression equations for the corresponding stations.

Very often, hourly precipitation records of sufficient length are not available. Even if they are available use of them to generate sequences of sufficient length would be costly. Hence, generation of daily rainfall transformed into monthly streamflow volumes may offer a useful tool for stochastic hydrology. The computation time would be within reasonablelimits for economic studies of water storage systems. Such an approach makes use of the largest data base - daily precipitation data.

This approach to generate streamflow through generation of rainfall assumes that the methodology used in generation of rainfall acounts adequately for the rainfall variability with respect to space, especially in the case of large catchments. Any model which generate rainfall at a single station would not give any result better than that given by a rainfall model which generates rainfall at more than one station.

One of the major assumptions in developing a stochastic multi-station rainfall model is that the generated rainfall can be adequately translated into streamflow. Therefore a rainfall runoff model should be developed which accounts for rainfall variability with respect to space in order to transform generated rainfall at several stations into streamflow at the outlet of the catchment.

2.4. REVIEW OF WORK ON RAINFALL RUNOFF RELATION

Nearly 300 years ago, in the years 1668, 1669 and 167 a French Scientist measured rainfall in the Seine river basin and found it to average about 520 mm per year. He estimated the runoff from the basin and found it to be only 1/6 of the rainfall. This is the first recorded quantitative experiment in rainfall-runoff relationships. Since then significant contributions have been made towards this aspect and they are contained in Mead's 'Hydrology'(1919) which offers a variety of empirical relationships for calculating monthly or annual volumesof runoff. Most of these take the form

$$R = KP - a$$

Where R is the annual runoff and P is the annual rainfall and a few of the relationships introduce temperature or humidity as parameters. Meyer (1915) appears to be the first who attempted at a rational calculation of runoff based on a physical conception of the hydrologic processes involved. He suggested a method to derive monthly and annual runoff values from rainfall and other physical data of the watershed and the same was applied to fifteen watersheds of widely varying characteristics.

The period of simple empiricism ended and modern hydrology begins with the work of Horton and Sherman in the early 1930's. Horton's paper on ' The Role of Infiltration in the Hydrologic Cycle ' (1931) and Sherman's paper ' Streamflow from Rainfall by the Unit Graph Method'(1932) represent together a milestone in hydrology. Since then the concept of the unit hydrograph hasbeen the subject of many papers in the technical literature. Out of those it would be appropriate to mention the work of Snyder (1938) on the development of synthetic unit hydrographs in which it was possible to describe key parameters of a unit hydrograph in terms of physical features of the watershed. Bernard (1935) presented the idea of the distribution graph - the unit hydrograph in histogram form. Morgan and Hullinghorst (1939) suggested the concept of the S-curve method for analyzing unit hydrographs. Another important contribution was made by Clark (1945) by which it was shown that the unit hydrograph may be obtained by routing the time area diagram. It was also shown how this concept may be used to derive accurate unit hydrographs for very short periods of initial runoff which accurately reflect the influence of shape of drainage area upon the shape of the hydrograph.

Okelly (1955) employed the unit hydrographs to determine the flows of Irish arterial drainage channels and demonstrated how the unit hydrograph may be used in problems of arterial drainage design. A method of constructing synthetic curves with catchment characteristics as parameters was also described.

In 1958, Nash presented his concept of the unit hydrograph as the end product of a series of successive linear storages in the watershed. Various methods of determining the relation between rainfall and runoff are examined and shown to be particular cases of the general unit hydrograph theory. A systematic approach to the investigation of the relation between the characteristics of a catchment and its response to rainfall was indicated.

In 1959 Dooge presented a paper giving a general equation for the unit hydrograph derived from the single physical assumption that the reservoir action which takes place in the catchment can be seperated from the translatory action and lumped in a number of reservoirs unrestricted in number, size or distribution.

The basic assumptions of the unit hydrograph and its many modifications are severe constraints on its utility. Basically the unit graph attempts to deal with a complex non-uniform input-excess rainfall which varies in time and area by considering it to be constant in time and uniform over area. This simplified input is assumed to be acted on by an invariant linear system of storages which is actually non-linear.

These limitations of unit hydrograph method compelled the researchers to go for more accurate and effective techniques of hydrologic modelling of runoff process.

The late 1950's brought a powerful new tool to the hydrologist - the digital computer. With its very high rate of arithmatic computation, the digital computer could do large masses of routine computation in short time intervals. Such computations would have taken years if done manually, consequently the computer made it possible to consider totally new approaches to dealing with hydrologic problems.

Computer analysis of hydrographs was attempted on a large scale. Sugawara (1961) hypothecated a complex system of linear storages and delays, and by successive trials, adjusted the system until rainfall input could be transformed to streamflow output with reasonable accuracy. His approach lacked generality, however, and an entirely new model had to be determined by trial for each watershed.

Nash (1959) undertook to fit hydrograph shapes to standard distribution equations by multiple regression between the appropriate equation, parameters and factors representing various physical characteristics of the watershed. O'Donnell (1965) attempted similar approach using Fourier Series.

Many researchers investigated the comparative use of above rainfall runoff models. In a recent paper by Sarma et al. (1973) the relative regeneration performances of five linear rainfall excess direct runoff models were compared for several urban watersheds with varying degrees of development.

The five models considered were the single linear reservoir, the Nash model, the double routing method, the linear channel linear reservoir model and the instantaneous unit hydrograph obtained by Fourier transform method. The IUH always gave the best regeneration performance among the models tested.

A significant departure from the other approaches and one which seems likely to lead ultimately to a general hydrologic model is the work of Crawford and Linsley (1960,62, 63, 66) in the development of the Stanford Watershed Model. This model which has gone through a substantial series of development phases is a simulation model of the hydrologic cycle. It is a moisture accounting procedure following on and amplifying an approach suggested by Linsley and Ackernann (1942). The inputs are hourly rainfall and daily potential evaportranspiration. The model outputs hourly streamflow anytime the flow is above a preselected base level, mean daily flow, total annual runoff, end-of-month soil moisture and ground water storages, actual evaportranspiration and other information. The model requires less than one minute of time on an IBM 7090 computer to generate a complete year of streamflow.

In 1971, the National Weather Service of U.S.A. decided to compile a National Weather Service River Forecast System. The concept of the system was that of a collection of hydrologic techniques which are comprehensive in scope and latest for operational purposes. On the basis of this a watershed model was developed in Sacremento, which was a modification of the Stanford Watershed Model. Advantage of this conceptual model is that it has been possible to attain accurate simulation of the past and also capable of predicting future events, specially the extreme events.

A very clear lesson from the water balance type of models is the importance of hourly rainfall input for most water sheds of less than 500 square miles. The short time interval rainfall data are seldom available for hydrological designs especially in developing countries where most of the catchments are yet ungaged.

Russian Scientists have been working on short range and long range river forecasting since 1919. A large number of papers on spring high-water forecasting were published between 1930 and 1940. Among them a prominent paper was by M.A.Velikanow who presented a study formulating the basic principles of the method of isochrones which has since evolved into one of the accepted methods of short range forecasting.

In the isochrone method, runoff is predicted by means of the genetic runoff formula, using the data on precipitation in the river basin. The isochrone method is applicable, as stated, only to basins having an area less than 20,000 $km.^2$

Mokliak (1958) suggested a method of construction of the unit hydrograph on the basis of isochrone method. In this method the unit hydrograph ordinates are calculated by specific genetic formula which is based on construction of isochrones after maximum velocity of water movement in the sections for a given time interval, and on transformation of the discharge in these sections by so-called lag coefficients.

The method which uses isochrones along with travel coefficients appears to be more realistic for catchments having limited observed data as it does not require sophisticated data. This method also considers the nonuniform distribution of rainfall with space, as well as the natural transformation of the discharge hydrograph during the process of movement along the length of the river system from the upper cross-sections to the lower outlet.

In the light of above discussion of the previous studies on stochastic modelling of rainfall runoff process, the following conclusions can be made. The synthesis of daily streamflow records is difficult to achieve directly, on account of the several difficulties involved in reproducing historic statistics in the generated sequences. Therefore any model that uses the daily rainfall data which constitutes the largest data base, to generate synthetic sequences of daily rainfall and then converts the same into daily streamflow by a suitable rainfall runoff relation can be expected to have the widest application. Such type of models have several other advantages. Among them is the ability of such models to predict modifications in the streamflow due to changes in the watershed such as urbanization without modyfying the generation model for rainfall. Moreover, the input to the model i.e. rainfall constitutes a reliable data base as it is not affected by watershed development. While recommending this type of approach to generate daily streamflow it may be stated the generation of daily rainfall which is subsequently converted to runoff must be carried out at several stations in order to account for the spatial variability of rainfall in computing the runoff. The model to be used to transform daily rainfall data to daily runoff depends upon the nature of data available. In a situation where the data available is very limited,which is the case in most developing countries a rainfall runoff model which uses isochrones and travel co-efficients can be one of the best models.

CHAPTER-3

THE PROPOSED STOCHASTIC DAILY STREAMFLOW MODEL

3.1. INTRODUCTION

The proposed stochastic daily streamflow model is comprised of two separate models.

1. A stochastic multi-station daily rainfall model.
2. A deterministic daily rainfall runoff model.

The methodology and the theoretical aspects on which the above models are based upon have been presented in the following sections of this Chapter

3.2. DEVELOPMENT OF THE STOCHASTIC MULTI-STATION DAILY PRECIPITATION GENERATION MODEL

Previous studies that have been carried out in this field have shown that there exists a considerable persistence of weather patterns, although precipitation amounts on successive days may not have significant correlation. The general characteristics of a series of daily rainfall observations are very much similar to those of Markov models. Therefore it would be pertinent here to describe the form of the Markov chain before going into the details of the stochastic multi-station daily precipitation model developed on the basis of previous studies on Markov models.

3.2.1. Markov Chains

A Markov chain can be described roughly as a process which evolves with time through a series of states in the following manner.

The probability law which governs the future development of the process at some point when it is in a given state depends only on that state and not on the prior evolution of the process. Such a process is called a First Order Markov Chain. If, however, the probability depends on the current state and also on the immediately preceeding state then it is called a second order Markov chain. This concept is formalised as follows.

A stochastic process $[X_t, t = 1,2, \ldots]$ is said to be an Nth order Markov chain if probability

$$P_r [X_t = x_t \mid X_{t-1} = x_{t-1}, \ldots X_1 = x_1]$$
$$= P_r [X_t = x_t \mid X_{t-1} = x_{t-1} \ldots X_{t-N} = x_{t-N}]$$

for all $x_1, x_2 \ldots\ldots x_t$ and $t = N+1, N+2 \ldots\ldots$ and if the X_t assumes discreet values.

For the first order Markov chain (i.e. $N = 1$)

$$P_r [X_t = x_t \mid X_{t-1} = x_{t-1}, \ldots X_1 = x_1]$$
$$= P_r [X_t = x_t \mid X_{t-1} = x_{t-1}]$$

3.2.2. Transition-Probability Matrix

Transition probabilities are the parameters that describe the probabilistic behaviour of a Markov chain. Transition probability $P_{ij}(t)$ is the probability that the process will be in state j at time t given that it was in state i at the previous step.

$$P_{ij}(t) = P_r \left[X_t = j \mid X_{t-1} = i\right]$$

In different words, the transition probability $p_{ij}(t)$ is the probability that the process will ' jump ' into state j at the time t if it is in state i at the time (t-1). In general this probability is a function of ' time'. If not, the process is said to be ' homogeneous' in time, in which case we write simply

$$p_{ij} = p_{ij}(t) \quad \text{for all } t$$

Transition probabilities are conveniently displayed in square arrays or matrices. It may have the following form.

State Left		State entered (0)	(1)	(2)
	(0)	p_{00}	p_{01}	p_{02}
	(1)	p_{10}	p_{11}	p_{12}
	(2)	p_{20}	p_{21}	p_{22}

Transition probability matrix has been satisfactorily used in generation of sequences of short time interval rainfall (Pattision, 1964). In such an application, the possible states, for example, could be as follows.

State	0	No rain
	1	Falls less than or equal to 1 mm
	2	Falls greater 1 mm

In the present study also, transition probabilities have been used to evaluate daily rainfall sequences at a network of three stations.

3.2.3. The Proposed Model

The proposed model has been designed to generate stochastic daily precipitation at a network of three stations on the lines of methodology suggested by Kraeger and using limited data of Naula catchment. The method evaluates the conditions, dry or wet, and if wet, the amount of precipitation. The method proceeds from the first station to the last station of the network in a given way.

The generation of rainfall at the first station is dependent on the precipitation states of the previous day at the first station and at two adjacent stations. The generation of rainfall at the second station depends on what occurred at first station on the same day and at the second and third stations on the previous day. The rainfall at the third station is generated from what occurred at first and second stations on the current day and at the third station on the previous day. In this manner the interrelationships of rainfall values among stations are preserved in the generated sequences.

Initially, the rainfall occurring during the year is examined to divide the year into statistically homogeneous seasons or periods. This may be done by plotting the five day average precipitation computed from the historic record for each station. Depending on the variability of rainfall during the year the number of periods to be considered may be less or more. Within a period, the dry-wet states and consequent rainfall amounts for each station-day are determined sequentially from station to station.

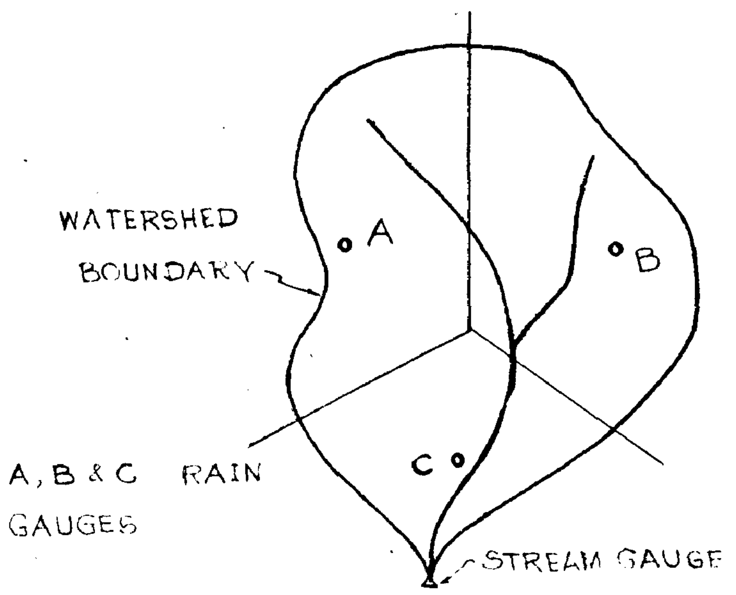

FIG. 3.1 THE MODEL WATERSHED

Let the network consists of only three precipitation stations as shown in figure 3.1. Only three stations are considered because of the large number of combinations of wet and dry probabilities possible. As the number of stations increases, the data are divided into smaller groups, so that parameter estimation of wet dry states would not be statistically significant. From the historic record, the frequency of wet days following wet days and dry days following dry days is developed for each combination of wet-dry states at all three stations.

3.2.3.1. <u>Model for First Station (A)</u>

All possible combinations of wet and dry states that are to be used for the first station are shown in Table 3.1.

Table 3.1

Time		Station B (t-1)	Station C (t-1)	Station A (t-1)	Station A (t-0)
Case	1	Wet	Wet	Wet	Wet or dry
	2	Wet	Wet	Dry	Wet or dry
	3	Wet	Dry	Wet	Wet or dry
	4	Wet	Dry	Dry	Wet or Dry
	5	Dry	Wet	Wet	Wet or dry
	6	Dry	Wet	Dry	Wet or dry
	7	Dry	Dry	Wet	Wet or dry
	8	Dry	Dry	Dry	Wet or dry

Figure 3.2. shows the above eight possible cases in the form of a flow diagram.

The historic record is examined and the frequency of occurance of each combination is tabulated against each case. For example, in case 1 above, the number of occurrences of A,B, and C at (t-1) wet and A at (t-0) wet divided by the total number of occurrances at A, B and C at (t-1) wet gives the observed frequency or the transition probability of a wet day following a wet day at station A. In the original study (Kraeger, 1971) it was necessary to employ a lag-four day model for the case eight in order t produce historic wet-dry sequence accurately. A fourth order model may not be necessary in all areas. As reported by Kraeger, by using the relationship in areas that can be defined adequately with a first order model, no significance will be lost.

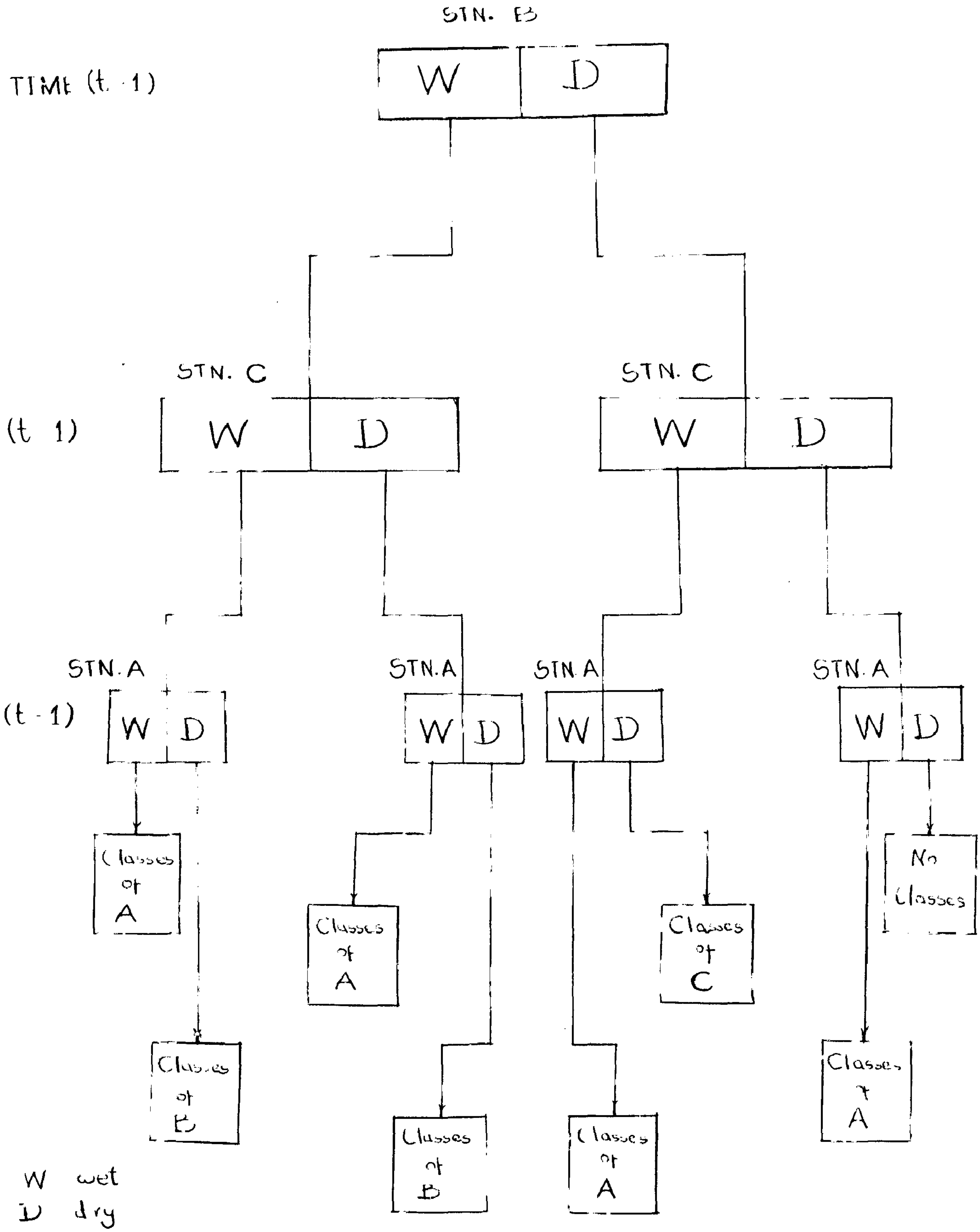

FIG 3 2

FLOW DIAGRAM FOR WET DRY COMBINATIONS AT STATION A

The procedure for generation is as follows. A uniformly distributed random number between zero and one is chosen. If the random number is less than the probability of rain, a wet day at station A willbe generated. If the random number is greater than the probability of rain, a dry day will be generated at station A and the model will move to station B and repeat the process. When a wet day is generated at the first station, the amount of precipitation is chosen from a cumulative frequency curve of historic daily precipitation by choosing another uniformly distributed random number between zero and one. An example of sampling from the cumulative distribution is shown in Figure 3.3.

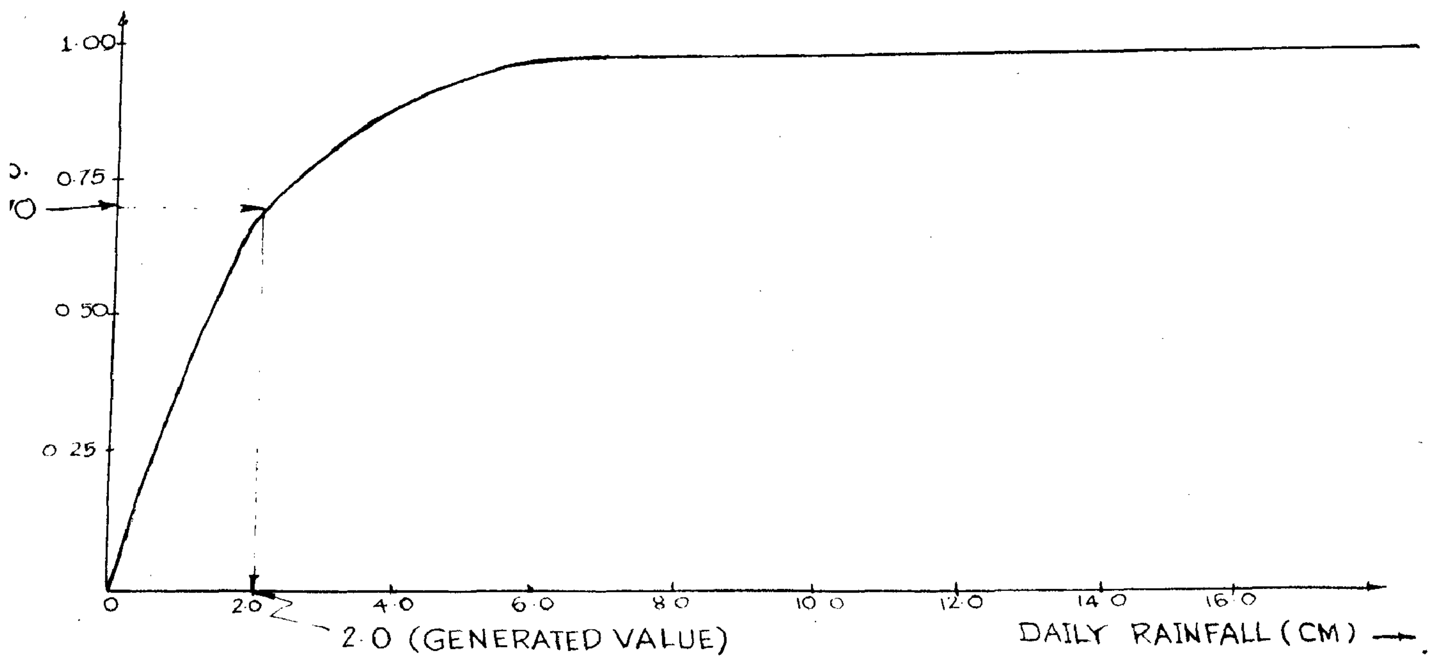

FIG.3.3 SAMPLING FROM CUMULATIVE FREQUENCY DISTRIBUTION

Sometimes the probability of a wet day following a wet day is dependent on the precipitation of previous day. Therefore it would not be correct to assume one probability value in each of the cases above, irrespective of what precipitation had occurred on previous day. Ideally, a continuous function should represent the change in probabilities of wet to wet states. Practically it would be very difficult to evaluate such a function and hence, in this model, the same effect has been accounted by evaluating the wet-dry probabilities for different predetermined levels of rainfall amount of the previous day at station A, B or C. Decision on number of levels and their boundary values should be made on the basis of initial experiments. The number of levels should not be too high to make the probability evaluated for each level unrepresentative.

3.2.3.2. Model for Second Station (B)

Once a wet or dry day, and consequent rainfall if any, has been generated at station A, the model moves to consider station B and does so in a manner similar to the procedure at station A. For station B also the transition matrix comprises of eight cases as that of station A. The development of the transition matrix for station B is illustrated by figure 3.4. By scanning the observed record one can estimate the number of occurances for each case and evaluate the transition probability for the same.

In this case the levels of rainfall amount at station A will be on the basis of the rainfall of current day. Thus, if station A had been wet, the rainfall at station A would be

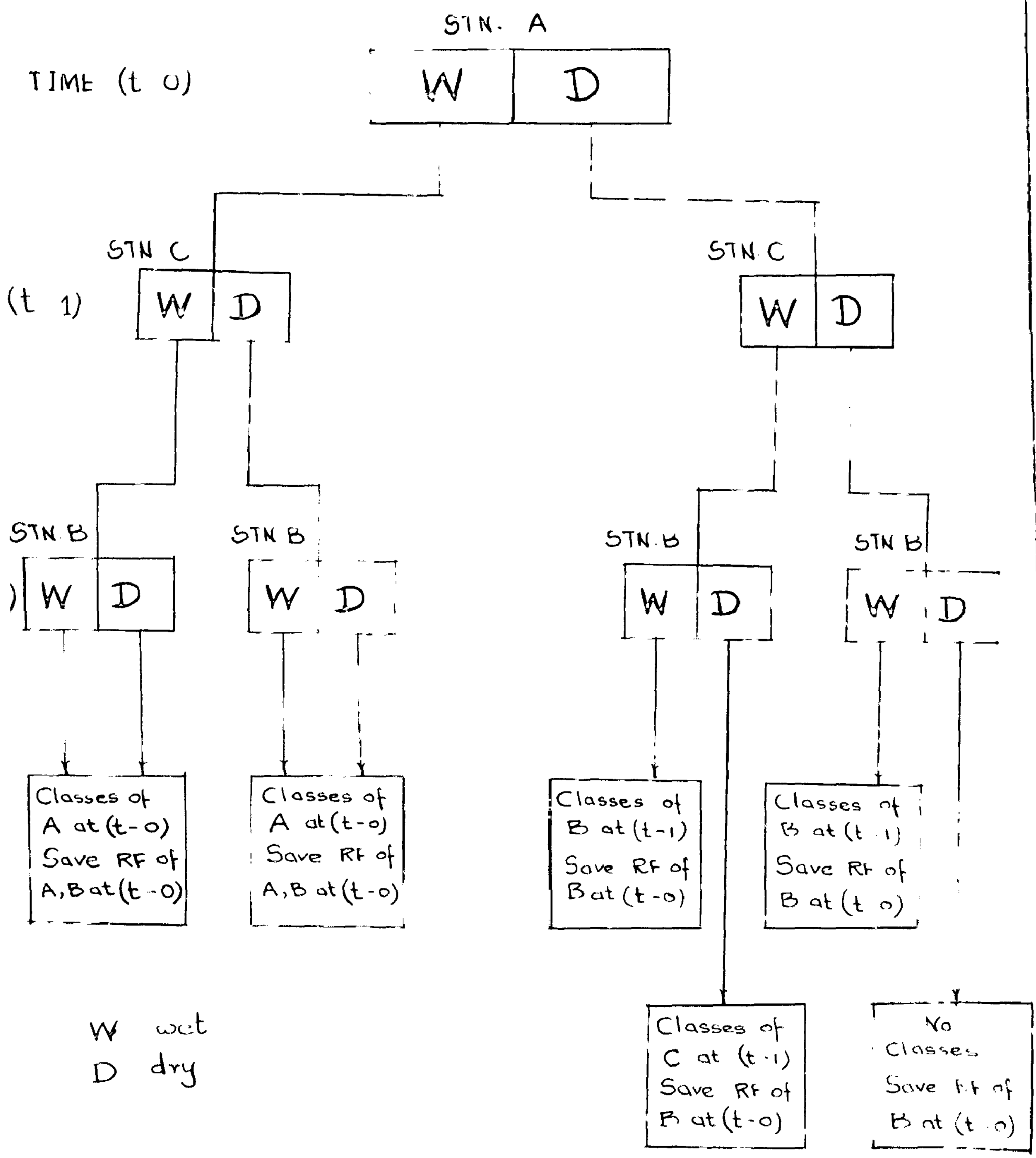

FIG 3.4

LOW DIAGRAM FOR WET - DRY COMBINATIONS AT STATION B used to choose the level of which, the probability would be used to generate a wet or dry day at station B. If station A were dry, but station B at time (t-1) were wet, then the magnitude of station B precipitation would be used to determine the level for the generation. If both A and B are dry on (t-0) and (t-1) days respectively and C is wet on (t-1) day, then station C precipitation would be used to select the level for generating a wet or dry day at B.

If a wet day has been generated at station B, the procedure to generate rainfall amount is different from that of station A. For example, if station B is wet and station A is also wet, a simple linear regression is used to relate the precipitation at station B to the precipitation at station A.
To develop this regression relationship, the daily rainfall data were transformed into a cumulative normal distribution with the help of historic cumulative precipitation curve. A separate regression is derived for each level in a particular case. This is assumed to approximate a non-linear correlation between rainfall stations.

To maintain the statistical variability between stations A and B, a normally distributed random component with a mean of zero and a variance equal to the historic variance from the regression analysis is added to the precipitation value calculated from the regression relationship.

Thus, the regression equation for each case and level is of the form

$$(\text{Station B}) = \alpha + \beta\,(\text{Station A}) + \varepsilon$$

where

α is the intercept

β is the slope of the regression equation

ε is a normally distributed random variable with the observed variance.

If A at (t-0) were dry and B were generated as wet (t-0) a uniformly distributed random number between zero and one would be chosen to sample from a conditional cumulative frequency curve of precipitation amounts at station B. This conditional cumulative frequency curve is to be developed from the non zero rainfall amounts at station B on the days when A is dry. This approach eliminates the probability of generating high precipitation values at B when A is dry.

3.2.3.3. Model for Third Station (C)

As for the first and second stations there can be eight cases of combinations of wet and dry states for the station C. The development of the transition matrix for the station C is shown in figure 3.5.

If both stations A and B are wet, only one rainfall amount, from either A or B, will be used to determine the wet-dry probability level for station C. If A is wet and B is dry, the magnitude of A will be used for levels. If A is dry and B is wet, the magnitude of B will determine the probability level at C. If both A and B are dry but C at (t-1) is wet, then the magnitude at station C previous day will determine the probability level.

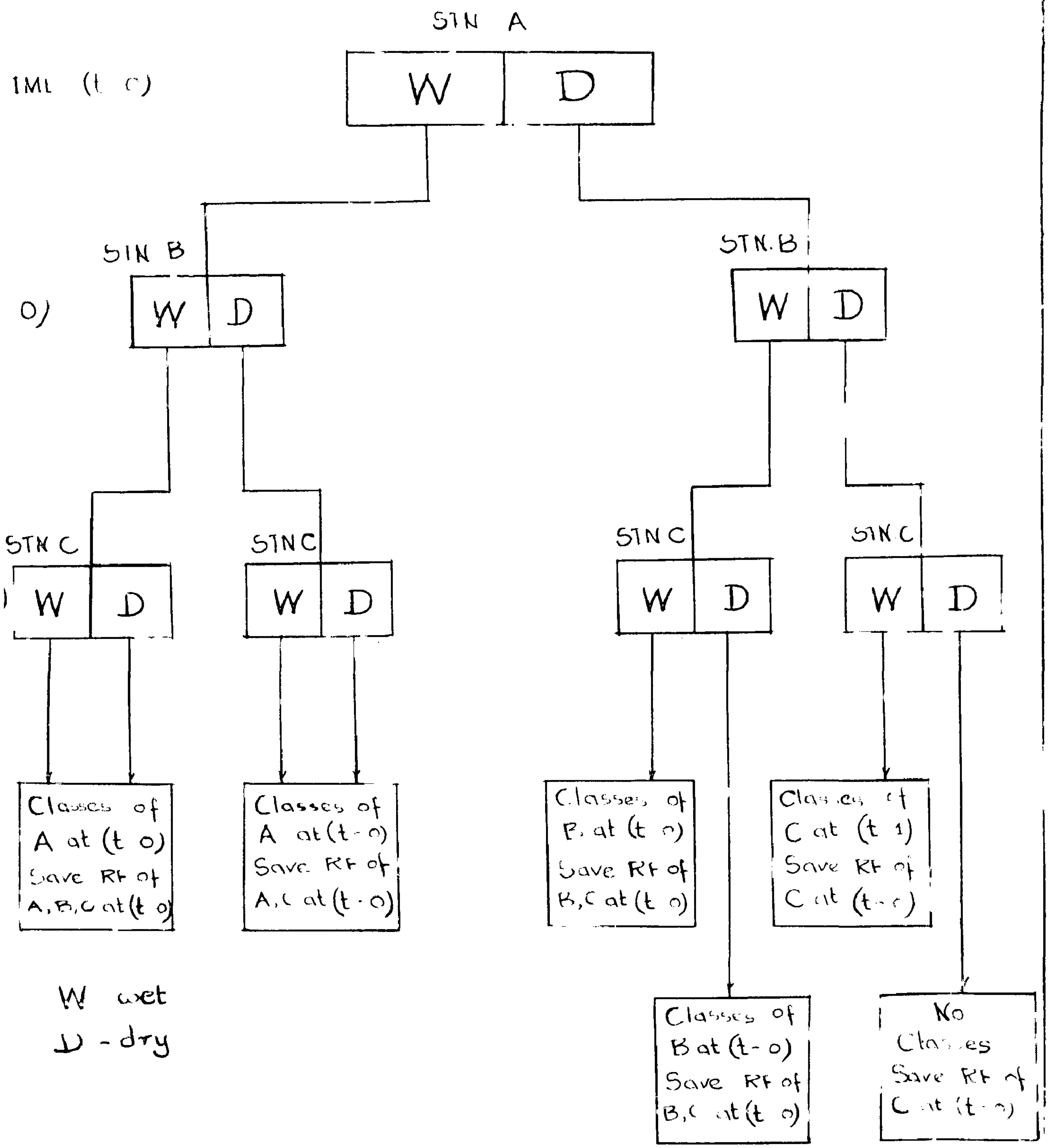

FIG 5 5

FLOW DIAGRAM FOR WET - DRY COMBINATIONS AT STATION C

If a wet day has been generated at C with wet days at A and B both, then the precipitation amount at station C would be determined by a multiple regression relationship of the form.

$$(\text{Station C}) = \alpha + \beta_1 (\text{Station A}) + \beta_2 (\text{Station B}) + \varepsilon$$

where

Stations A, B and C are the transformed daily rainfall amounts

α is the intercept

β_1 regression coefficient for station A

β_2 regression coefficient for station B

ε is a normally distributed random component with the observed variance.

When station A is wet but B is dry the regression equation would be of the form

$$(\text{Station C}) = \alpha + \beta_1 (\text{Station A}) + \varepsilon$$

when station A is dry but B is wet the regression equation would be of the form

$$(\text{Station C}) - \alpha + \beta_2 (\text{station B}) + \varepsilon$$

If both stations A and B are dry but C is wet at (t-0), the rainfall amount at C is chosen randomly from a cumulative frequency curve of rainfall amounts occurring at C when both stations A and B are dry.

The three models described above constitute the stochastic multi-station daily precipitation generation model.

3.3. DEVELOPMENT OF THE DETERMINISTIC RAINFALL RUNOFF MODEL

The deterministic rainfall runoff model has been developed in two stages, namely -

1) The division of entire catchment into sub areas on the basis of isochrones.
2) The determination of travel coefficient for each sub-area to account for the transformation of discharges within inter-isochrone sections.

3.3.1. Theoretical background

The outflow hydrograph at the outlet of a catchment due to any storm is characterized by seperable watershed translation and storage effects. Pure translation of the direct runoff to the outlet via the drainage network is described using the channel travel time, resulting in an outflow hydrograph that ignores watershed storage effects.

To apply the method proposed in this study, the basin is first divided into a number of time zones, seperated by isochrones. Isochrones are the lines of equal travel time from the watershed outlet. The areas between isochrones plotted against travel time in the form of a histogram constitute the time-area diagram. This diagram may be viewed as the outflow hydrograph due to translation effect alone, as mentioned above. An example is shown in figure 3.6.

There is no simple, rigorous means of deriving the time area diagram, it is usually assumed that travel time is proportional to channel distance from each point to the outflow station, possibly taking variations in slope into account.

Therefore in this study the travel time is assumed to be proportional to $l/S^{1/2}$, where

l is the length of the channel and

S is the slope of the channel

In this method one drawback is the necessity of deriving the total travel time accurately.

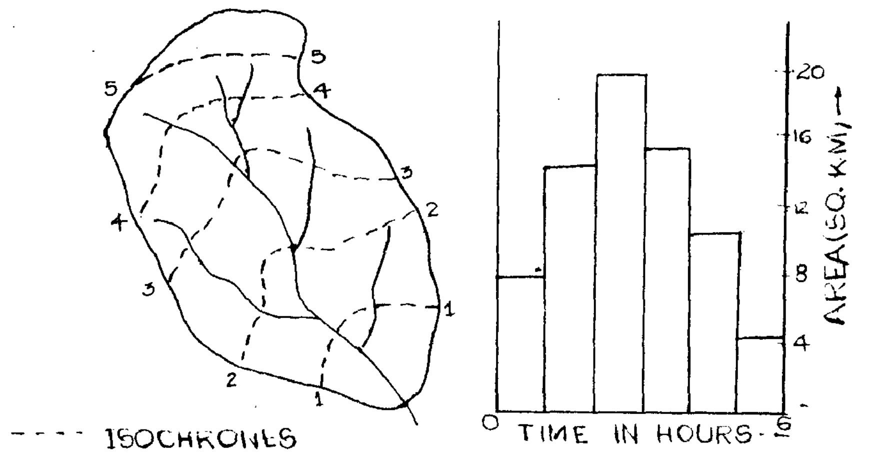

FIG. 3.6 TIME AREA DIAGRAM FOR A CATCHMENT

The basis of the method given herein to transform the discharge within inter-isochrone sections is the genetic runoff formula

$$Q_T = \sum_{i=1}^{i=n} f_i \; h_{T-(i-1)\Delta t}$$

where

Q_T is the mean discharge at the outlet at time T

h is the effective depth of precipitation

Δt is the time unit considered for precipitation increments.

n is the number of isochrones covering the entire catchment at Δt time interval, representing the run-off time lag on the channel system. When the water yield h_1 is observed during one time-interval only, discharges at the outlet are determined by the formulae,

$$Q_1 = h_1 f_1, \; Q_2 = h_1 f_2, \; Q_3 = h_1 f_3, \text{ etc.}$$

Such an approach to determine the discharges at the outlet cannot be considered correct, as the natural transformation of the discharge hydrograph during the process of movement along the length of the river system from the upper cross-sections to the lower outlet is neglected.

It is generally accepted that specific features of the hydrographic network pattern affect the inflow from the slopes to the river system only, i.e., the discharges at the individual isochrones at the first (initial) time interval. Thereafter the discharges are transported and transformed by the unsteady regime of the flow.

Because individual particles of water move in the river channels with different velocities, the discharge $Q_1 = h_1 f_1$ formed on the sub watershed area f_1 will not pass through the outlet simultaneously, but in a distributed manner. During the first day the portion will be equal to $r_1^{(1)}$, during the second day it will be equal to $r_2^{(1)}$, during the third day it will be equal to $r_3^{(1)}$ and so on. Under the condition of no losses in the channel and flood plain of the river, the sum of coefficients $r^{(1)}$ will be a unity, that is

$$\sum_{i=1}^{i=m} r_i^{(1)} = 1$$

The index on r shows the number of the watershed on which the discharge Q was formed, and the suffix shows the number of days from the beginning of calculation.

The discharge Q_2 formed on the subwatershed area f_2 will be under way during the first day, and during the second day the portion of this discharge $r_2^{(2)}$ will pass through the outlet, during the third day the portion will be $r_3^{(2)}$ and so on. The sum of travel coefficients $r^{(2)}$ as mentioned above will also be equal to unity.

i.e., $\sum_{i=2}^{i=n} r_i^{(2)} = 1$. The discharges $Q_3 = h_1 f_3, Q_4$ etc. are all subject to the same distribution. The scheme of calculation for the hydrograph ordinates is shown in Table 3.2.

Table 3.2

Scheme of Calculation of the Hydrograph Ordinates

). of ubwater ned	Catchment areas	Discharge of the surface inflow	Elements of discharges according to the time-intervals				
			1	2	3	4	5
	f_1	$Q_1=h_1f_1$	$r_1^{(1)} Q_1$	$r_2^{(1)} Q_1$	$r_3^{(1)} Q_1$	.	.
	f_2	$Q_2=h_1f_2$	.	$r_2^{(2)} Q_2$	$r_3^{(2)} Q_2$	$r_4^{(2)} Q_2$	$r_5^{(2)} Q_2$
	f_3	$Q_3=h_1f_3$	.	.	$r_3^{(3)} Q_3$	$r_4^{(3)} Q_3$	$r_5^{(3)} Q_3$
	.	.	.	.	.	.	.
)tal	F	$Q= h_1F$	q_1	q_2	q_3	q_4	q_5

Summing up individual discharges which reach the outlet at the same time we obtain the final values of the hydrograph of discharge at the outlet. Similar calculations could be carried out for the other rainfall excess elements.

Now, comes the problem of evaluating travel coefficients for individual subwatershed area.

Let the initial travel coefficient be r and let us assume that it is constant for all the sub-areas.

For the first area the proportion of discharge appearing at the outlet on the first day = r.

Proportion of water remaining in sub-area = (1-r)

Proportion of water released on second day = r x(1-r)

Proportion of water released on third ay = r x [(1-r) x (1-r)]

$$= r\,(1-r)^2$$

In general, proportion of water released on the day t

$$= r\,(1-r)^{t-1} \quad \text{for } t \geq 1$$

For the second area water appears only on the second day for the first time and the proportion appearing on second day (after accounting the transformation taking place in first area)

$$= r \times r$$

Proportion appearing at the outlet on third day (after accounting the portion from the water in first area also)

$$= r \times r \times (1-r) + r \times (1-r) \times r$$

$$= 2\,r^2\,(1-r)$$

In general, proportion of water appearing on the day t

$$= (t-1)\,r^2\,(1-r)^{t-2} \quad \text{for } t \geq 2$$

The general expression for travel coefficients for individual sub area may be given as

$$r_t^{(\tau)} = \frac{(t-1)!}{(\tau-1)!(t-\tau)!} \quad r^{\tau} (1-r)^{t-\tau}$$

It is not correct to assume same initial travel coefficient r for all the sub water sheds, specially when topography is varying along the length of the river.

In a similar manner described above, it can easily be shown that the travel coefficients for the individual sections between isochrones for different values of the initial travel coefficients are given by

$$r_t^{(\tau)} = (1- r_1^{(\tau)}) \, r_{t-1}^{(\tau)} + r_1^{(\tau)} \, r_{t-1}^{(\tau-1)}$$

where $r_1^{(\tau)}$ is the initial travel coefficient for the sub-watershed area τ.

Some typical values of travel coefficients for a watershed of 4 days travel time with different initial travel coefficient is shown in Table 3.3.

Table 3.3

Travel Coefficients for a watershed of 4 days lag time

Subarea initial coeff.		1 0.55	2 0.60	3 0.80	4 0.90
Day	1	0.5500	0.0000	0.0000	0.0000
	2	0.2475	0.3300	0.0000	0.0000
	3	0.1114	0.2805	0.2640	0.0000
	4	0.0501	0.1790	0.2772	0.2376
	5	0.0225	0.1017	0 1986	0.2732
	6	0.0101	0.0542	0.1211	0.2061
	7	0.0045	0.0277	0.0676	0.1296
	8	0.0020	0.0138	0.0357	0.0738

It has been found that for ordinary rivers of plains $r \approx 0.7-0.8$, for rivers having a large flood plain $r \approx 0.5-0.6$, for marshy and over grown stretches of rivers $r \approx 0.35-0.45$ (Mokliak, 1967).

3.3.2. The Proposed Model

Some typical observed hydrographs of the historic record are analyzed to determine the magnitude of the basin lag time The approach that has been suggested in this model is to evaluate the values of n and K in the Nash model and to compute the product nK which approximately indicate the basin lag. However the basin lag time may be retained as a parameter to be optimized through the computer model, thereby the necessity of determining the lag time accurately may be avoided.

The isochrones are drawn at desired intervals, by the procedure described in section 3.3.1.

Approximate valuesof initial travel coefficients are determined by the initial experiments carried out on the selected typical hydrographs. The final values to be adopted to generate synthetic sequences of daily streamflow are to be optimized through the computer model by treating them as parameters of the rainfall-runoff model.

The distribution of rainfall within the day is also assumed to be a model parameter. This may not be necessary if the historic record consist of rainfall data observed at short time intervals less than a day. However in such cases it may be necessary to derive models for storm duration as well as inter-storm periods, to be included in the generation model. Very often the situation is such that only daily rainfall data are available and it becomes necessary to assume some empirical distribution within the day.

3.3.2.1. Model for Daily Rainfall excess

On account of the complexity involved in various phases of rainfall-runoff process it is very difficult to derive an accurate model for the daily rainfall excess. In water balance type rainfall runoff models it has been achieved through the book-keeping of soil moisture in various zones of the upper soil layer.

In this model the run-off coefficient approach has been suggested to compute daily rainfall excess, which can be easily included in the generation model. Initially the runoff co-efficient is computed for all the typical storms selected from the historic record and related to the following parameters.

1. Antecedent Precipitation Index (API)
2. Amount of rain
3. Duration of storm
4. Week Number

The relationship may be obtained through stepwise multiple regression technique, for both ordinary and logarithmic transformed values of the above variables. The appropriate relationship may be selected on the basis of multiple correlation co-efficient and standard error.

3.3.2.2. Model for Baseflow component

In order to complete the stochastic daily streamflow model it was necessary to develop a separate model for the base flow component of daily streamflow. For this purpose the method that has been suggested in this study is to develop an empirical curve of baseflow versus direct runoff on the basis of values obtained from some typical storms of observed record. However the application of this model to compute daily values of base-flow component has to be checked.

3.3.3. Comparison of Observed and Simulated Hydrographs

There is no unique method of comparing the observed and the regenerated direct runoff hydrographs. Besides the qualitative comparisons based on visual observation, peak reduction etc. certain statistical measures such as,

1) The correlation coefficient, R
2) The Integral Square Error, ISE
3) Efficiency, E (Nash and Sutchliffe, 1970) may be used.

The expressions for the above parameters are as follows -

$$R = \frac{N \Sigma Q_o Q_c - (\Sigma Q_o)(\Sigma Q_c)}{\sqrt{[(N \Sigma Q_o^2 - (\Sigma Q_o)^2][N \Sigma Q_c - (\Sigma Q_c)^2]}}$$

$$ISE = \frac{[\Sigma (Q_o - Q_c)^2]}{\Sigma Q_o}$$

$$E = \frac{\Sigma (Q_o - \bar{Q}_o)^2 - \Sigma (Q_c - Q_o)^2}{\Sigma (Q_o - \bar{Q}_o)^2}$$

where

Q_o = Observed runoff

Q_c = Computed runoff

N = Number of values

In this model the coefficient of efficiency given by the last expression is used for comparison of observed and simulated direct runoff hydrographs. In this expression the term $\Sigma (Q_o - \bar{Q}_o)^2$ represents the observed variance and the term $\Sigma (Q_c - Q_o)^2$ represents the residual or unexplained variation. The value of this statistic will always be less than unity.

3.3.4. Suitability of the Proposed Model

The model that has been proposed is suitable for many situations varying from instances where the available data is very limited to instances where much sophisticated data is available. However the model was developed especially for a situation where the available data is limited, such as that of Naula catchment of Ramganga basin. The advantage of this model as against other well known rainfall runoff models is that the number of parameters to be optimized is less, which tends to yield reliable estimates of parameters especially with limited data.

CHAPTER-4

DATA ASSEMBLY AND APPLICATION OF THE PROPOSED MODEL

4.1. INTRODUCTION

The proposed model as described in Chapter-3 was tested using limited data of a catchment having observed records of daily values of major hydrologic variables viz. rainfall and streamflow. The rainfall model has been found to generate synthetic sequences of daily rainfall with the observed statistics reproduced in the generated sequences, provided the length of the observed record is adequate to define the model parameters accurately (Kraeger 1971). As suggested by Kraeger(1971) about thirty years of precipitation data have to be used to define the model parameters adequately.

Very often designers face the problem of inadequate data. The reliability of available data is also doubtful. One of the main objectives of this study was to investigate, the possibility of applying this model to such a situation where the data available is only for a short period.

4.2. CATCHMENT CHARACTERISTICS

The catchment selected for this study belongs to the Ramganga river basin in Uttar Pradesh, India. Ramganga river is the first main tributary of Ganga river on its left, after the river enters the plains. The catchment of Ramganga river upstream of a multipurpose dam at Kalagarh extends over a rugged and hilly terrain of 3120 sq.km. Most of the area falls in the outer and middle Himalayan regions but a smaller part of it is in the Himalayan foothills and Siwaliks.

The catchment under study covers an area of 1130 sq.km. of the Ramganga Catchment, upto Naula gauge site. The Naula subcatchment with its main tributory is shown in Figure 4.1.

Some other data which would explain the nature of the Naula catchment are as follows.

Average slope	=	42.306 percent
Mean elevation	=	1621 meters
Drainage density	=	3.221 km/km^2
Percentage of dense forest	=	40.04 percent
Percentage of thin forest	=	7.38 percent
Percentage of dense shrub	=	1.72 percent
Percentage of thin shrub	=	9.18 percent
Agricultural lands	=	24.20 percent
Grass lands	=	12.13 percent
Area under mixed land uses	=	5.35 percent

4.3. AVAILABLE DATA

Daily rainfall data at six rain gauges inside the catchment for the period of six years from 1970 to 1975 are available. Only the total daily values are available and information about within the day variation could not be procured. Six rain gauge stations at which the rainfall records are available, along with their Thiessen weightages are given in Table 4.1

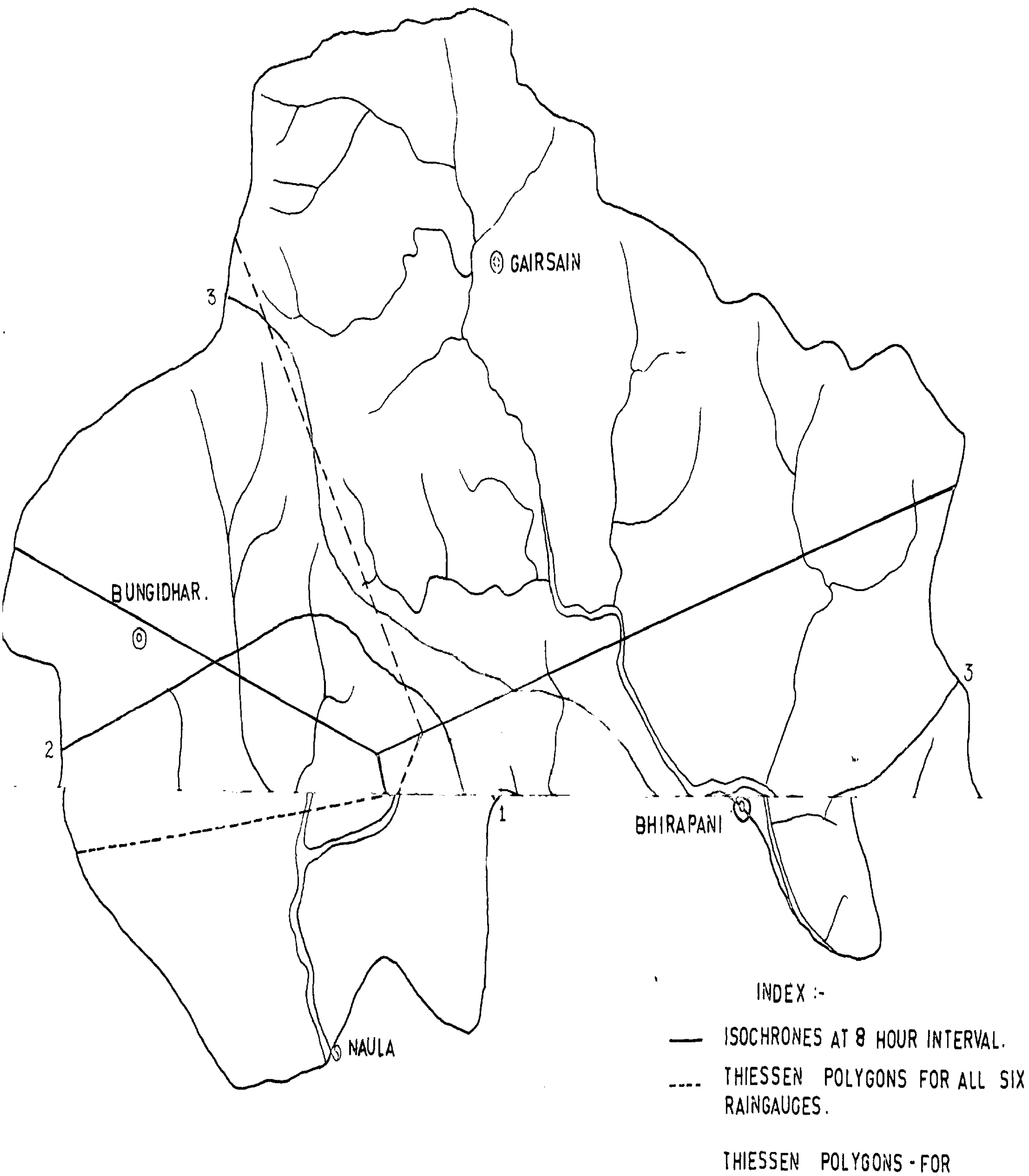

FIG. 4.1: NAULA CATCHMENT DIVIDED INTO ISOCHRONES & THIESSEN POLYGONS.

Table 4.1

Station	Thiessen Weightage
Choukhutia	0.2733
Gairsain	0.2391
Naula	0.0813
Tama dhawn	0.1859
Bungidhar	0.1512
Bhirapani	0.0689

Daily runoff data of Ramganga river at Naula gauge site are available for the period, April 1970 to December 1975.

4.4. CALIBRATION OF STOCHASTIC MULTI-STATION DAILY PRECIPITATION MODEL

The procedure described in Chapter-3 has been followed in deriving the parameters for the daily precipitation model. Detailed computations and the results obtained at each stage are given in the following sections of this chapter.

4.4.1. Statistically homogeneous periods

The rainfall record at Choukhutia which has the highest Thiessen weightage out of six rain gauge stations was investigated to derive the homogeneous periods. For this, five days average precipitation during the period 1970 to 1975 was plotted as a histogram, against the months as shown in Figure 4.2. Six periods were chosen by carefully inspecting the plot of historic five day average percipitation and they were as follows.

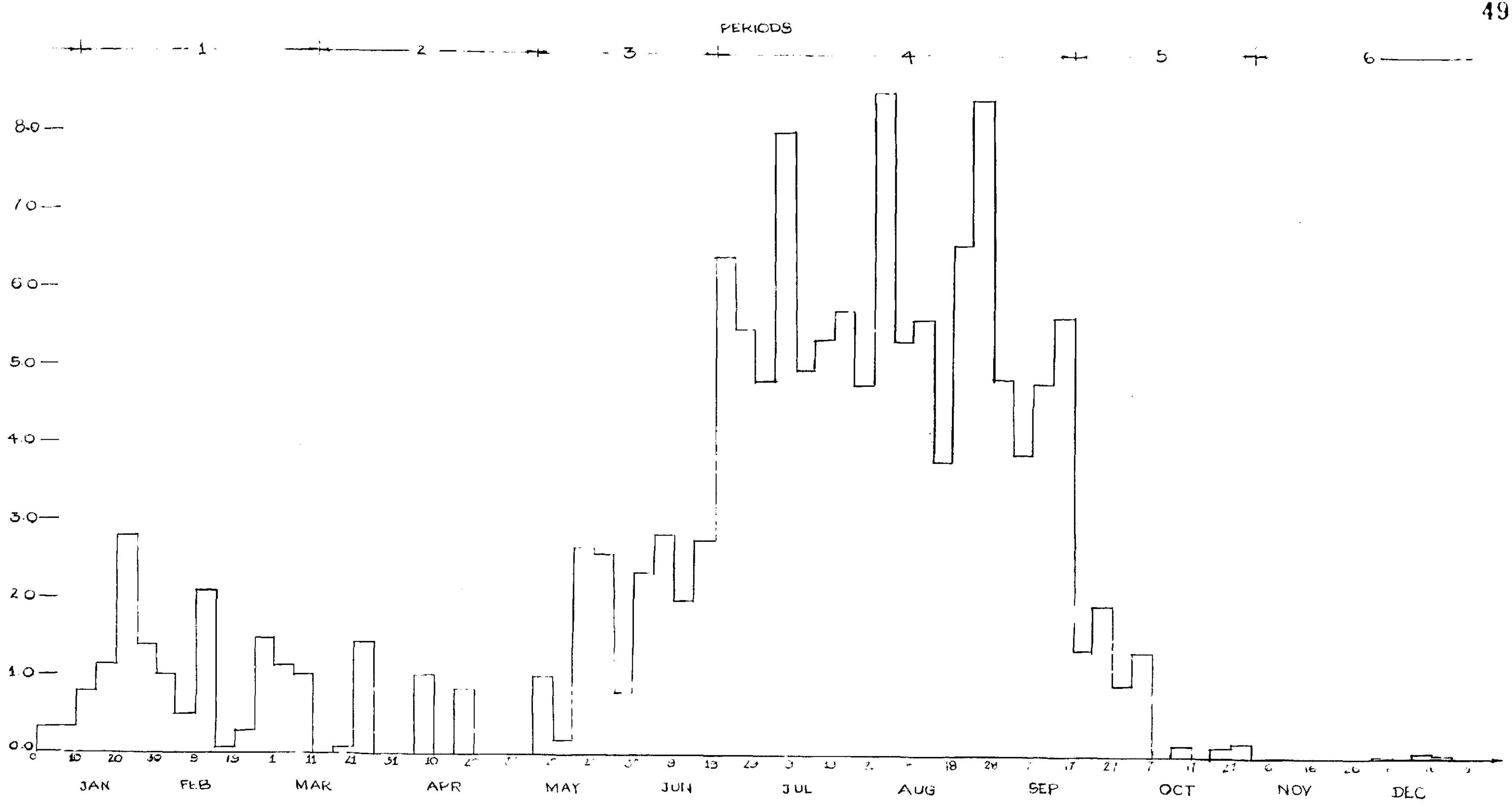

FIG 4.2

HISTORIC FIVE DAY AVERAGE PRECIPITATION, CHOUKHUTIA 1970 1975

Period	1	January, 11 to March ,11
	2	March,12 to May, 5
	3	May, 6 to June, 19
	4	June , 20 to September, 17
	5	September, 18. to November, 1
	6	November, 2 to January, 10

For the sake of simplicity only the monsoon period i.e. June,20 to September,17 was chosen for further analysis.

4.4.2. Selection of three stations

Among the six rain gauge stations for which the daily rainfall data are available, it was necessary to select three stations to be used in the stochastic daily rainfall model. For this purpose the variation of annual rainfall at each station was investigated as shown in Figure 4.3 The mean annual rainfall against each rain gauge station is listed in the Table 4.2.

Table 4.2

Mean Annual Rainfall

Rain gauge station	Mean Annual Rainfall(cms)
Choukhutia	139.23
Gairsain	162.72
Naula	89.45
Tamadhawn	99.14
Bungidhar	168.15
Bhirapani	121.45

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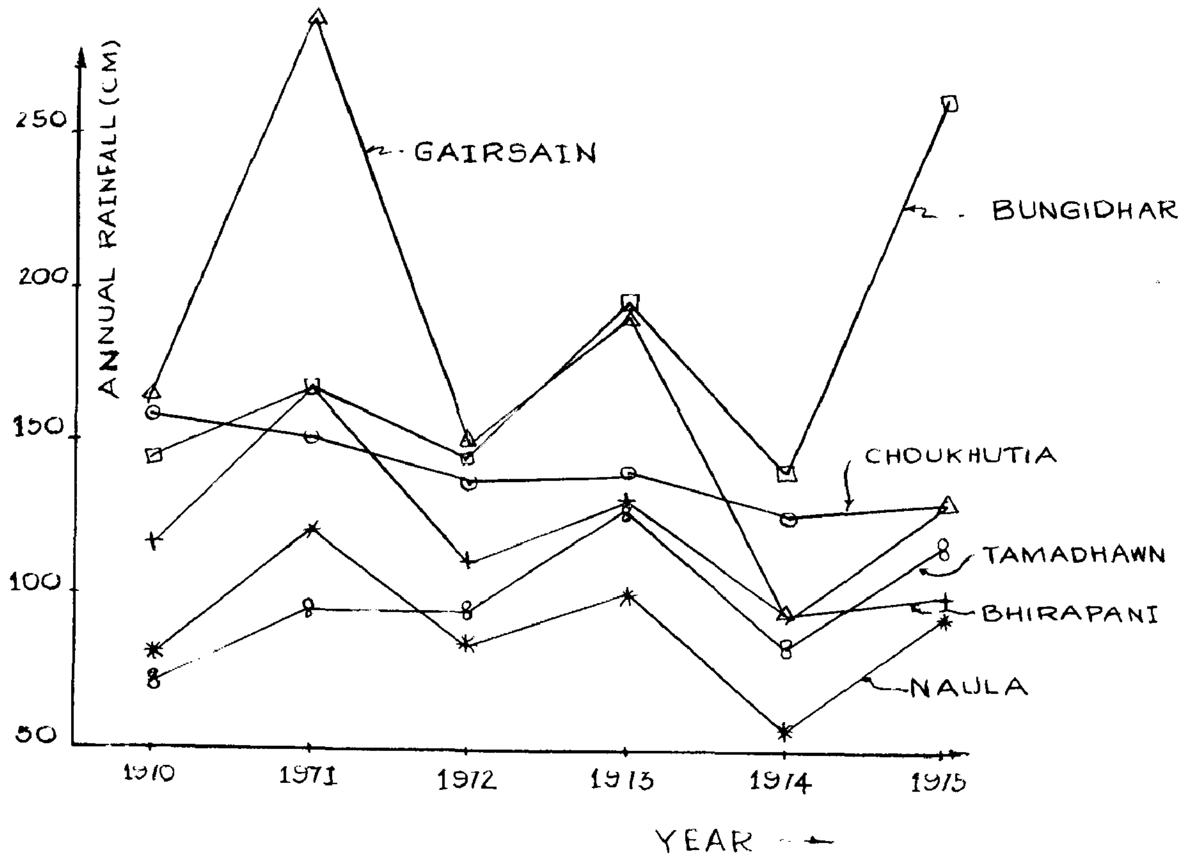


FIG. 4.3

VARIATION OF ANNUAL RAINFALL

The stations that are selected should adequately **define the** average rainfall over the catchment. On the basis of following results the stations Choukhutia, Gairsain and Tamadhawn were selected for the model.

Arithmatic mean of all six gauges = 130.018 cms.

Arithmatic mean of the selected three stations = 133.69

Thiessen mean of all six gauges = 136.45 cms.

Thiessen mean using only the selected three stations = 133.084

The Thiessen weightages for the selected stations are as follows -

Station	Thiessen weightage
Choukhutia	0.37144
Gairsain	0.29970
Tamadhawn	0.32885

4.4.3. Historic Cumulative Frequency Curves

A computer program was run to determine the cumulative frequency distribution for all three stations. The results of the computer program are shown in Table 4.3. The curves are shown in figure 4.4.

4.4.4. Levels of Rain

In order to decide upon number of levels and their boundary values some initial experiments were carried out on historic data at all 3 stations. One of them was to plot the probability of wet day following a wet day with (t-1) day

Table 4.3

Historic Cumulative frequency distribution of Stations A,B, and C (Choukhutia, Gairsain and Tamdhawn respectively)

Sl. No.	Class inter-val	STATION A		STATION B		STATION C	
		Cumula-tive no. of events	Cumula-tive frequency	Cumulative no. of events	Cumula-tive frequn-cy	Cumula-tive no. of events	Cumula-tive frequency
	0.0-0.1	24	0.0701	25	0.0659	10	0.0392
	0.1-0.2	44	0.1286	43	0.1134	28	0.1098
	0.2-0.3	70	0.2046	65	0.1715	44	0.1725
	0.3-0.4	85	0.2485	87	0.2295	64	0.2509
	0.4-0.5	103	0.3011	109	0.2875	78	0.3058
	0.5-0.6	112	0.3274	121	0.3192	93	0.3646
	0.6-0.7	127	0.3713	132	0.3482	102	0.3999
	0.7-0.8	143	0.4181	145	0.3825	114	0.4470
	0.8-0.9	149	0.4356	158	0.4168	120	0.4705
	0.9-1.0	160	0.4678	175	0.4617	131	0.5137
	1.0-2.0	242	0.7075	273	0.7203	188	0.7372
	2.0-3.0	273	0.7982	325	0.8575	223	0.8745
	3.0- 4.0	296	0.8654	343	0.9050	236	0.9254
	4.0-5.0	314	0.9181	355	0.9366	242	0.9490
	5.0-6.0	324	0.9473	365	0.9630	245	0.9607
	6.0-7.0	334	0.9765	372	0.9815	249	0.9764
	7.0-8.0	338	0.9882	374	0.9867	252	0.9882
	> - 8	342	1.0000	379	1.0000	255	1.0000

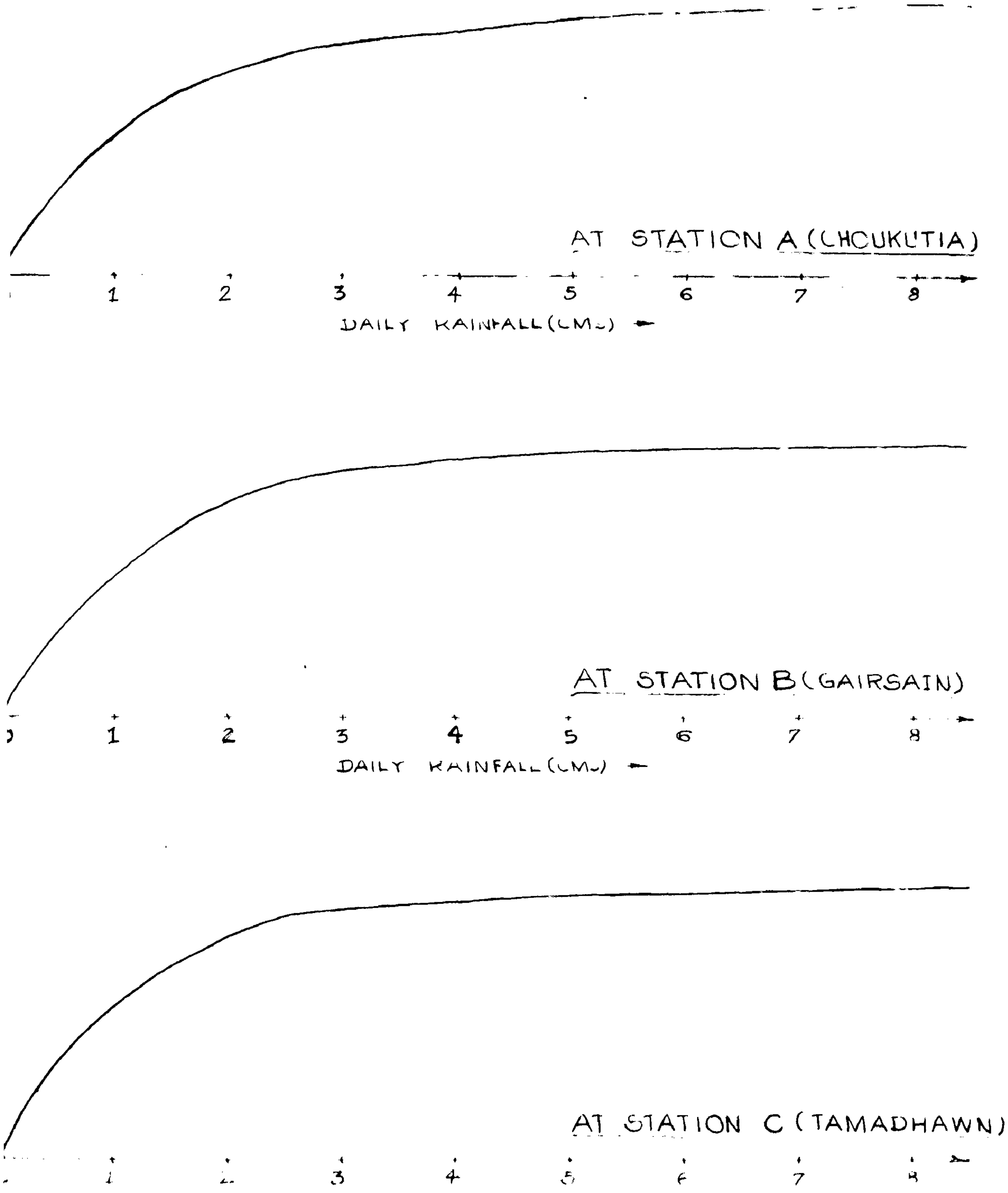


FIG 4.4 HISTORIC CUMULATIVE FREQUENCY CURVES AT STATIONS A, B & C

having different magnitudes of rain against the intervals of rain as shown in figure 4.5. Although this does not indicate clearly the levels to be chosen, approximately three levels were chosen as follows.

Level	Interval of rain
1	0 - 1.5 cms.
2	1.5 - 5.5 cms.
3	5.5 cms. and above

More number of levels would make the transition probabilities unrepresentative,as the number of values falling in each class would be very less on account of limited data being used. Therefore only 3 levels were chosen for this data of Naula catchment.

4.4.5. Wet-dry Probabilities for three Stations

Computer programs were developed to evaluate the wet-dry probabilities for all the three stations. On account of limited capacity of the IBM - 1620 computer available for the use, it was not possible to combined all three stations together. The wet- dry probabilities for the three stations as obtained from the computer programs are shown in Tables 4.4, 4.5 and 4.6.

Provisions have been made in the computer programs to derive conditional cumulative frequency of daily rainfall at rain gauge stations B and C. The tables 4.7 and 4.8 show the results obtained. Figure 4.6 shows the conditional cumulative frequency curves.

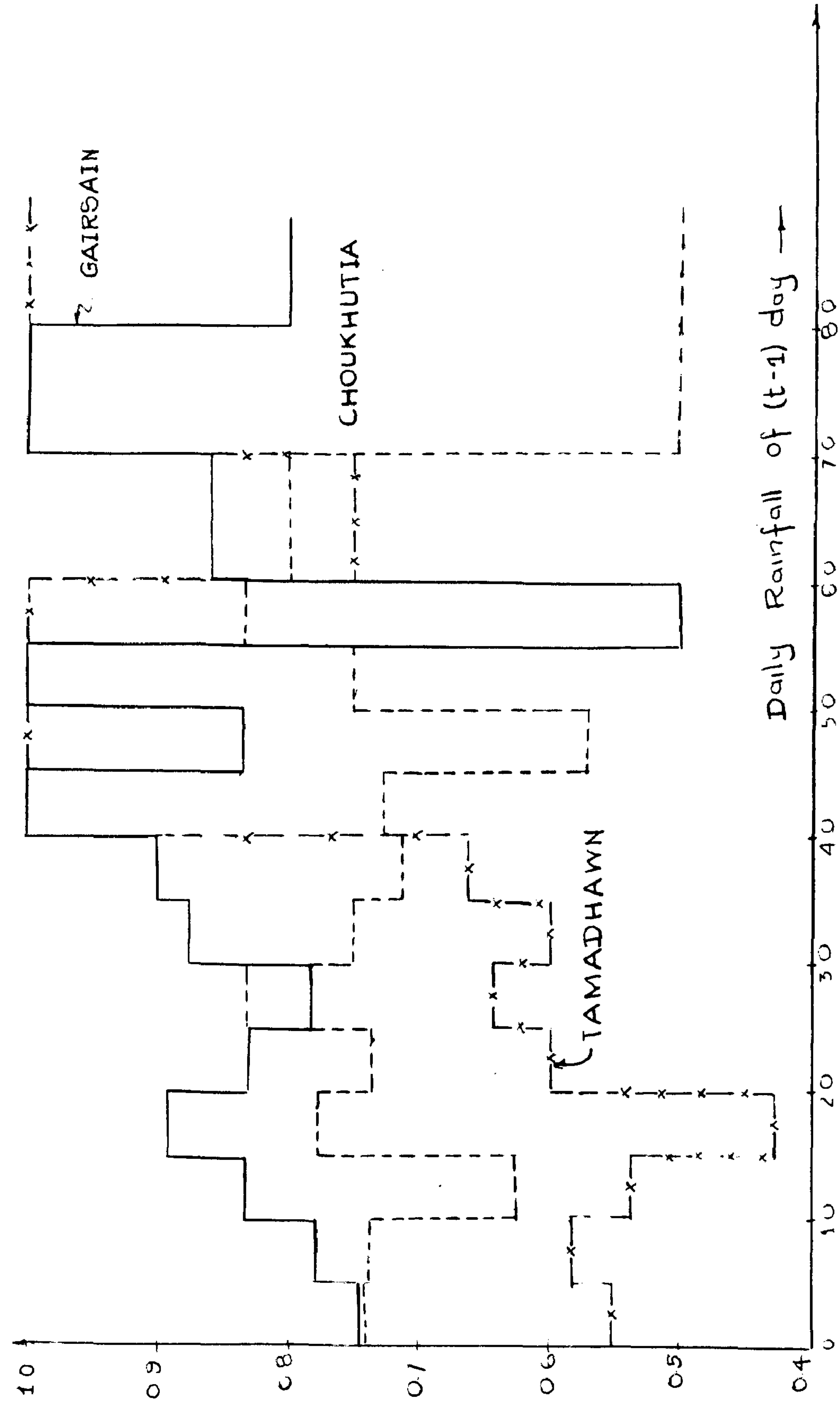


FIG 4.5 PROBABILITY OF WET DAY FOLLOWING A WET DAY AT EACH STATION

Table 4.4

Probability of Wet days following Wet or Dry days at Ist Station (A)

Cases	Level of Rain at A at time t-1	B t-1	C t-1	A t-1 to t-0	A t-1 to t-0	Probability of rain at A
	cms.	Wet	Wet	Wet to wet	Wet to dry	
1	0.025 to 1.5			64	16	0.8000
	1.5 to 5.5			52	18	0.7428
	5.5 and above			12	5	0.7058
2		Wet	Dry	Wet to wet	Wet to dry	
	0.025 to 1.5			49	14	0.7777
	1.5 to 5.5			18	8	0.6923
	5.5 and above			6	3	0.6666
3		Dry	Wet	Wet to wet	Wet to dry	
	0.025 to 1.5			11	4	0.7333
	1.5 to 5.5			5	2	0.7142
	5.5 and above			0	0	0.0000
4		Dry	Dry	Wet to wet	Wet to dry	
	0.025 to 1.5			23	23	0.5000
	1.5 to 5.5			5	0	1.0000
	5.5 and above			2	0	1.0000
5	Level of rain at B at time t-1	Wet	Wet	Dry to wet	Dry to dry	
	0.025 to 1.5			18	10	0.6428
	1.5 to 5.5			12	0	1.0000
	5.5 and above			4	4	0.5000
6		Wet	Dry	Dry to wet	Dry to dry	
	0.025 to 1.5			21	23	0.4772
	1.5 to 5.5			5	6	0.4545
	5.5 and above			1	0	1.0000
7.	Level af rain at C at time t-1	Dry	Wet	Dry to wet	Dry to dry	
	0.025 to 1.5			2	12	0.1428
	1.5 to 5.5			0	1	0.0000
	5.5 and above			0	0	0.0000
8.	No levels	Dry	Dry	Dry to wet	Dry to Dry	
				26	49	0.3466

Table 4.5

Probability of wet days following wet or dry days at 2nd station (B)

Level of Rain At A at time t-0 cms.	A t-0	C t-1	B t-1 to t-0	B t-1 to t-0	Probability of Rain at B
	Wet	Wet	Wet to wet	Wet to dry	
0.025 to 1.5			71	16	0.8160
1.5 to 5.5			56	5	0.9180
5.5 and above			13	1	0.9285
	Wet	Dry	Wet to wet	Wet to dry	
0.025 to 1.5			47	13	0.7833
1.5 to 5.5			27	2	0.9310
5.5 and above			10	1	0.9090
Level of rain at B at time t-1	Dry	Wet	Wet to wet	Wet to dry	
0.025 to 1.5			20	11	0.6451
1.5 to 5.5			7	8	0.4666
5.5 and above			5	2	0.7142
	Dry	Dry	Wet to wet	Wet to dry	
0.025 to 1.5			20	20	0.5000
1.5 to 5.5			12	1	0.9230
5.5 and above			1	0	1.0000
Level of Rain at A at time t-0	Wet	Wet	Dry to wet	Dry to dry	
0.025 to 1.5			7	7	0.5000
1.5 to 5.5			2	0	1.0000
5.5 and above			2	0	1.0000
	Wet	Dry	Dry to wet	Dry to Dry	
0.025 to 1.5			16	24	0.4000
1.5 to 5.5			11	4	0 7333
5.5 and above			1	0	1.0000
Level of rain at C at time t-1	Dry	Wet	Dry to wet	Dry to dry	
0.025 to 1.5			10	7	0.5882
1.5 to 5.5			1	1	0.5000
5.5 and above			0	0	0.0000
No levels	Dry	Dry	Dry to wet	Dry to dry	
			29	43	0.4027

Table 4.6

Probability of wet days following wet or dry days at 3rd station (C)

	Level of Rain at A at time t-0	A t-0	B t-0	C t-1 to t-0	C t-1 to t-0	Probability of Rain at C
ses	Cms.	Wet	Wet	Wet to wet	Wet to wet	
	0.025 to 1.5			52	26	0.6666
	1.5 to 5.5			44	14	0.7586
	5.5 and above			9	6	0.6000
		Wet	Dry	Wet to wet	Wet to Dry	
	0.025 to 1.5			6	17	0.2608
	1.5 to 5.5			4	1	0.8000
	5.5 and above			0	1	1.0000
	Level of rain at B at time t-0	Dry	Wet	Wet to wet	Wet to Dry	
	0.025 to 1.5			15	15	0.5000
	1.5 to 5.5			5	4	0.5555
	5.5 and above			4	0	1.0000
	Level of rain at C at time t-1	Dry	Dry	Wet to wet	Wet to dry	
	0.025 to 1.5			7	12	0.3684
	1.5 to 5.5			2	8	0.2000
	5.5 and above			0	0	0.0000
	Level of rain at A at time t-0	Wet	Wet	Dry to Wet	Dry to dry	
	0.025 to 1.5			27	36	0.4286
	1.5 to 5.5			26	12	0.6842
	5.5 and above			8	3	0.7272
		Wet	Dry	Dry to wet	Dry to dry	
	0.025 to 1.5			8	29	0.2162
	1.5 to 5.5			3	3	0.5000
	5.5. and above			0	1	1.0000
	Level of rain at B at time t-0	Dry	Wet	Dry to wet	Dry to dry	
	0.025 to 1.5			14	29	0.3256
	1.5 to 5.5			7	7	0.5000
	5.5 and above			4	1	0.8000
	No levels	Dry	Dry	Dry to wet	Dry to dry	
				7	57	0.1094

Table 4.7

Observed conditional cumulative frequency of daily Rainfall

At B, (GAIRSAIN)

(Rainfall at B (time t-0)/ No rainfall at A(time t-0))

Sl.No.	Class Interval	Cumulative No. of events	Frequency
1	0-0.1	5	0.0476
2	0.1-0.2	15	0.1428
3	0.2-0.3	20	0.1905
4	0.3-0.4	28	0.2666
5	0.4-0.5	33	0.3143
6	0.5-0.6	40	0.3809
7	0.6-0.7	44	0.4190
8	0.7-0.8	45	0.4285
9	0.8-0.9	48	0.4571
10	0.9-1.0	49	0.4666
11	1.0-2.0	84	0.8000
12	2.0-3.0	91	0.8666
13	3.0-4.0	95	0.9048
14	4.0 and above	105	1.0000

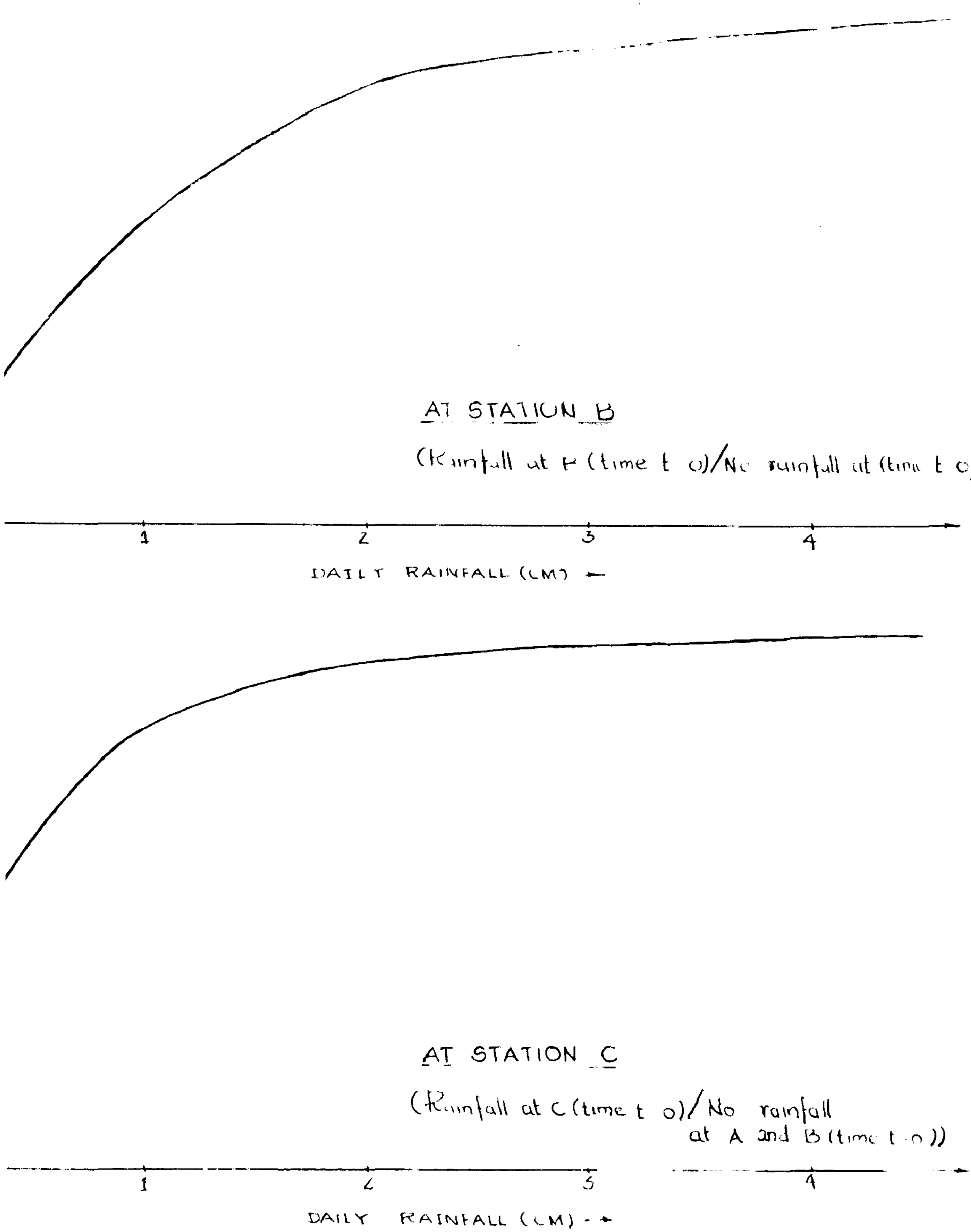
Table 4.8

Observed conditional cumulative frequency of daily rainfall

At C, (TAMADHAWN)

(Rainfall at C (time t-0)/ No rainfall at A or B (time t-0))

Sl.No.	Class Interval	Cumulative No. of events	Frequency
1	0 - 0.1	4	0.2500
2	0.1-0.2	6	0.3750
3	0.2-0.3	7	0.4375
4	0.3-0.4	8	0.5000
5	0.4-0.5	8	0.5000
6	0.5-0.6	9	0.5625
7	0.6-0.7	11	0.6875
8	0.7-0.8	13	0.8125
9	0.8-0.9	13	0.8125
10	0.9-1.0	13	0.8125
11	1.0-2.0	15	0.9375
12	2.0-3.0	15	0.9375
13	3.0-4.0	16	1.0000
14	4.0 and above	16	1.0000



.6 CONDITIONAL CUMULATIVE DISTRIBUTIONS AT B AND C

4.4.6. Regressions relations among stations

The rainfall values falling in each case of wet-dry combinations were seperately listed by the above programs. A computer program was developed to convert these rainfall figures into a cumulative normal distribution by assuming a series of straight line segments representing the historic cumulative precipitation curves derived above. Another computer program determines the regression relations and the necessary statistical parameters for all bivariate cases of all three stations. Another computer program for multiple regression which had been developed earlier was used for multivariate cases (when more than two stations are involved). The results of these programs have been summarized in Tables 4.9 and 4.10. It is seen from these tables that the correlation co-efficient in many of the cases is very less. This can be attributed to the limited data that was used to develop the same.

4.5. APPLICATION OF THE MODEL TO GENERATE STOCHASTIC DAILY RAINFALL

The model was used to generate synthetic sequences of daily rainfall for the monsoon season. For this purpose a computer program was developed with all model parameters derived above as input data and the same was run in a IBM 360/44 computer. The computer model is designed in such a way that the generation of magnitude of rainfall at any station would be achieved through sampling from the historic cumulative frequency curve, if the correlation coefficient for the

Table 4.9

Linear Regression Relationship Developed From Transformed Daily Rainfall at A and B

ases	Level of Rain at A at time t-0 cms	A t-0 wet α	C t-1 Wet β	B t-0 to t-0 Wet to wet Correlation	Variance
	0.025 to 1.5	0.34000	0.35413	0.20377	0.88614
	1.5 to 5.5	-0.12252	0.55327	0.19573	0.73507
	5.5 and above	-0.72400	0.89408	0.38622	1.00183
		A t-0 Wet α	C t-1 Dry β	B t-1 to t-0 Wet to wet Correlation	Variance
	0.025 to 1.5	0.18583	-0.04684	0.02990	0.68676
	1.5 to 5.5	-0.45071	0.92124	0.35581	0.66763
	5.5 and above	2.86385	-1.29967	0.31495	0.61698
		A t-0 Wet α	C t-1 Wet β	B t-1 to t-0 Dry to wet Correlation	Variance
	0.025 to 1.5	-0.73740	-1.29589	0.54928	0.62885
	1.5 to 5.5	0	0	0	0
	5.5 and above	0	0	0	0
		A t-0 Wet α	C t-1 Dry β	B t-1 to t-0 Dry to wet Correlation	Variance
	0.025 to 1.5	-0.33676	-0.47172	0.30902	0.77628
	1.5 to 5.5	0.51127	-0.50097	0 16844	0.67792
	5.5 and above	0	0	0	0

Table 4.10

Regression Relationship Developed from Transformed Daily Rainfall at A, B, and C

Cases	Level of Rain at A at time t-0 cms.		A t-0 Wet	B t-0 Wet	C t-1 to t-0 Wet to wet	
1		α	β_1	β_2	Correlation	Variance
	0.025 to 1.5	0.1764	0.3905	0.2005	0.34863	0.66514
	1.5 to 5.5	0.3778	0.1756	0.0387	0.08256	0.69844
	5.5 and above	1.1196	-0.2236	0.7650	0.76706	0.51278
2			A t-0 Wet	B t-0 Dry	C t-1 to t-0 Wet to wet	
		α	β_1		Correlation	Variance
	0.025 to 1.5	0.1851	0.0810		0.02968	1.03524
	1.5 to 5.5	-1.7370	2.1766		0.30705	1.65610
	5.5 and above	0.0	0.0		0.0	0.0
3.	Level of rain at B at time t-0		A t-0 Dry	B t-0 Wet	C t - 1 to t- 0 Wet to wet	
		α		β_2	Correlation	Variance
	0.025 to 1.5	0.0045		-0.3300	0.25331	0.64286
	1.5 to 5.5	-0.5016		-0.6992	0.11419	0.47938
	5.5 and above	-5.5772		3.1340	0.71221	1.26624
4.	Level of Rain at A at time t-0		A t-0 wet	B t-0 wet	C t - 1 to t-0 Dry to wet	
		α	β_1	β_2	Correlation	Variance
	0.025 to 1.5	0.0900	-0.0257	0.3480	0.28687	0.70163
	1.5 to 5.5	0.2563	-0.3367	0.1712	0.19388	0.65169
	5.5 and above	-1.1464	0.4311	0.9866	0.42827	1.47483
			A t-0 Wet	B t-0 Dry	C t-1 to t-0 Dry to wet	
		α	β_1		Correlation	Variance
	0.025 to 1.5	-0.3462	-0.6475		0.61401	0.48101
	1.5 to 5.5	1.2821	-1.0506		0.99943	0.00028
	5.5 and above	0.0	0.0		0.0	0.0
	Level of Rain at B at time t-0		A t-0 Dry	B t-0 Wet	C t-1 to t-0 Dry to wet	
		α		β_2	Correlation	Variance
	0.025 to 1.5	0.0287		0.1458	0.12238	0.60974
	1.5 to 5.5	0.8928		-0.8305	0.62425	0.16375
	5.5 and above	1.4552		-0.4954	0.026386	0.75773

regression relationship by which the actual generation is to be done is insignificant with respect to a predetermined level of significance. Therefore, it was possible to carryout the generation of daily rainfall for the entire period desired, through sampling from the cumulative frequency distributions. In the light of these provisions made in the computer model, the following alternatives were attempted in order to make a comparative study of the performance of the model.

(1) Synthetic sequences of lengths 5 years, 25 years and 100 years were generated and the significance level for correlation coefficients was kept at 0.100 so that the generation was predominantly through regression relations.

(2) Synthetic sequences of lengths 5 years, 25 years and 100 years were generated with the significance level of correlation coefficient being very high so that the entire generation procedure was through sampling from cumulative frequency distributions.

Table 4.11 lists some statistics of daily rainfall of observed and generated sequence of 5 years for the case (1) above.

Table 4.12 shows the mean daily rainfall, mean season rainfall and standard deviation of mean season rainfall for both observed and three generated sequences at all stations in case (1) above. Table 4.13 lists the same statistics for the same sequences for case (2) above.

Table 4.11

Statistics of observed and generated sequence of 5 years

Year	Station No.	Observed sequence Mean (cms)	Observed sequence Std.dev. (cms)	Observed sequence Skewness	Generated sequence Mean (cms)	Generated sequence Std.dev. (cms)	Generated sequence Skewness
1	1	1.158	1.843	2.167	1.314	1.794	1.758
	2	1.133	1.504	2.003	1.339	2.334	4.274
	3	0.480	1.104	4.153	0.850	2.438	5.542
2	1	1.530	2.140	1.545	1.053	2.053	3.888
	2	1.597	2.011	2.187	1.207	1.884	2.579
	3	0.543	1.035	3.836	0.696	0.971	2.172
3	1	1.253	2.227	3.110	0.971	1.536	2.386
	2	1.220	1.908	3.318	1.264	1.646	3.103
	3	0.763	1.602	3.498	0.817	1.390	3.168
4	1	1.206	1.801	1.896	1.014	1.767	2.358
	2	1.490	1.724	1.781	1.169	2.239	4.074
	3	1.037	1.707	2.977	0.470	0.786	2.367
5	1	0.845	1.232	2.504	1.013	1.481	2.032
	2	0.693	1.380	5.062	1.037	1.677	3.577
	3	0.676	1.369	2.752	0.552	1.160	5.407

Table 4.12

Statistics of Observed and Generated Sequences(Case (1))

(a) Mean Daily Rainfall (cms.)

Station No.	Observed	Generated 5 year	25 year	100 year
1	1.1595	1.0730	0.9962	0.9632
2	1.2006	1 2032	1.0337	1.0237
3	0.7470	0.6770	0.6072	0.6068

(b) Mean Season Rainfall (cms.)

Station No.	Observed	Generated 5 year	25 year	100 year
1	104.36	96.57	89.66	86.69
2	108.07	108.29	93.04	92.14
3	67.22	60.93	54.65	54.62

(c) Std. Dev. of Mean Season Rainfall (cms.)

Station No.	Observed	5 year	Generated 25 year	100 year
1	21.48	12.40	16.67	17.85
2	29.03	10.15	20.01	19.59
3	20.45	14.81	14.24	16.63

Table 4.13

Statistics of Observed and Generated Sequences(Case(2))

(a) Mean Daily Rainfall (cms.)

Station No.	Observed	Generated 5 year	Generated 25 year	Generated 100 year
1	1.1595	1.039	0.9379	1.0076
2	1.2006	0.9105	1.0074	0.9954
3	0.7470	0.6405	0.5553	0.6035

(b) Mean Season Rainfall (cms.)

Station No.	Observed	Generated 5 year	Generated 25 year	Generated 100 year
1	104.36	93.51	84.41	90.69
2	108.07	81.95	90.67	89.59
3	67.22	57.65	49.98	54.32

(c) Std. Dev. of Mean Season Rainfall(cms.)

Station No.	Observed	Generated 5 year	Generated 25 year	Generated 100 year
1	21.48	27.05	12.29	18.65
2	29.03	17.37	15.49	18.25
3	20.45	15.66	15.05	15.27

4.6. CALIBRATION OF DAILY RAINFALL RUNOFF MODEL

The calibration of Daily Rainfall-Runoff model was carried out in two stages.

1. Derivation and drawing of isochrones on the watershed.
2. Determination of travel coefficients and other model parameters through optimization.

Intermediate computations and results are presented in following sections.

4.6.1. Basin travel time

The travel time through the basin should be computed on the basis of the average streamflow velocity in the channel network, possibly taking variations in slope into account. In catchments such as Naula catchment where the variation of topography is rapid along the length of the river, it is not possible to assume a single value for average streamflow velocity. Furthermore, reliable estimates of streamflow estimates for varying conditions are not available in literature.

The correct approach would be to compute the translation time in two stages as follows -

1. The time of overland flow
2. The time of flow through the river channel

Due to the difficulties stated above, it was decided to estimate time of travel through the basin by some indirect way. In this situation the best approach would be to extract whatever information possible, from the observed record. In the light of this, several isolated observed storms were investigated by the procedure suggested by Nash (1958). The values of n and K in the Nash model were computed and the finally accepted values on the basis of the best storm(intense, uniformly distributed and covers the entire catchment) are as follows.

$$n = 3.9896$$

$$K = 0.3287 \text{ days}$$

$$nK = 1.3116 \text{ days}$$

The values of n and K have been computed by the following formulae as given by Nash.

$$M_{DRH1} - M_{ERH1} = nK$$

$$M_{DRH2} - M_{ERH2} = n\ (n+1)\ K^2 + 2nK\ \ M_{ERH1}$$

where M_{DRH1} and M_{ERH1} are the first moments of effective rainfall hyetograph and direct runoff hydrograph respectively and M_{DRH2} and M_{ERH2} are the second moments of the same.

The value of nK which is the distance to the centroid of instantaneous unit Hydrograph from the origin, represents the time delay due to translation. Therefore for the Naula catchment it was assumed that the total translation time is equal to 1.3116 days, approximately 32 hours. However provision has been made to treat this also as a parameter of the model which may be optimized.

4.6.2. <u>Subdivision of Catchment by Isochrones</u>

The time interval at which isochrones were to be drawn was assumed as 8 hours. The travel time from the outlet was computed for individual points along the main stream and tributaries, according to the method proposed in section 3.3.1. Contours of equal travel time were drawn at an interval of 8 hrs. as shown in Fig.4.1. The time area diagram ordinates as obtained from the Fig.4.1 have been listed in Table 4.14.

Table 4.14

Time-area diagram ordinates

Isochrone Number	Time(hours)	Area(sq.km.)
1	0-8	103.05
2	8-16	341.72
3	16-24	341.48
4	24-32	343.75

4.6.3. Trial values of initial travel coefficients

The values of initial travel coefficients must be derived through initial experiments so that the initial guess may be close to the actual values for sub areas. For this purpose it was decided to simulate the one day unit hydrograph derived from Instantaneous Unit Hydrograph with the n and K values determined above. Various combinations of initial travel coefficients were used in several simulation trials. The coefficient of efficiency obtained for each simulation trial is listed in Table 4.19.

The trial no.3 gives the best combination of initial travel coefficients and for this set derived and simulated unit hydrographs are shown in Figure 4.7. Consequently, this set was selected to be the best combination of initial travel coefficients, which is to be optimized through the computer model.

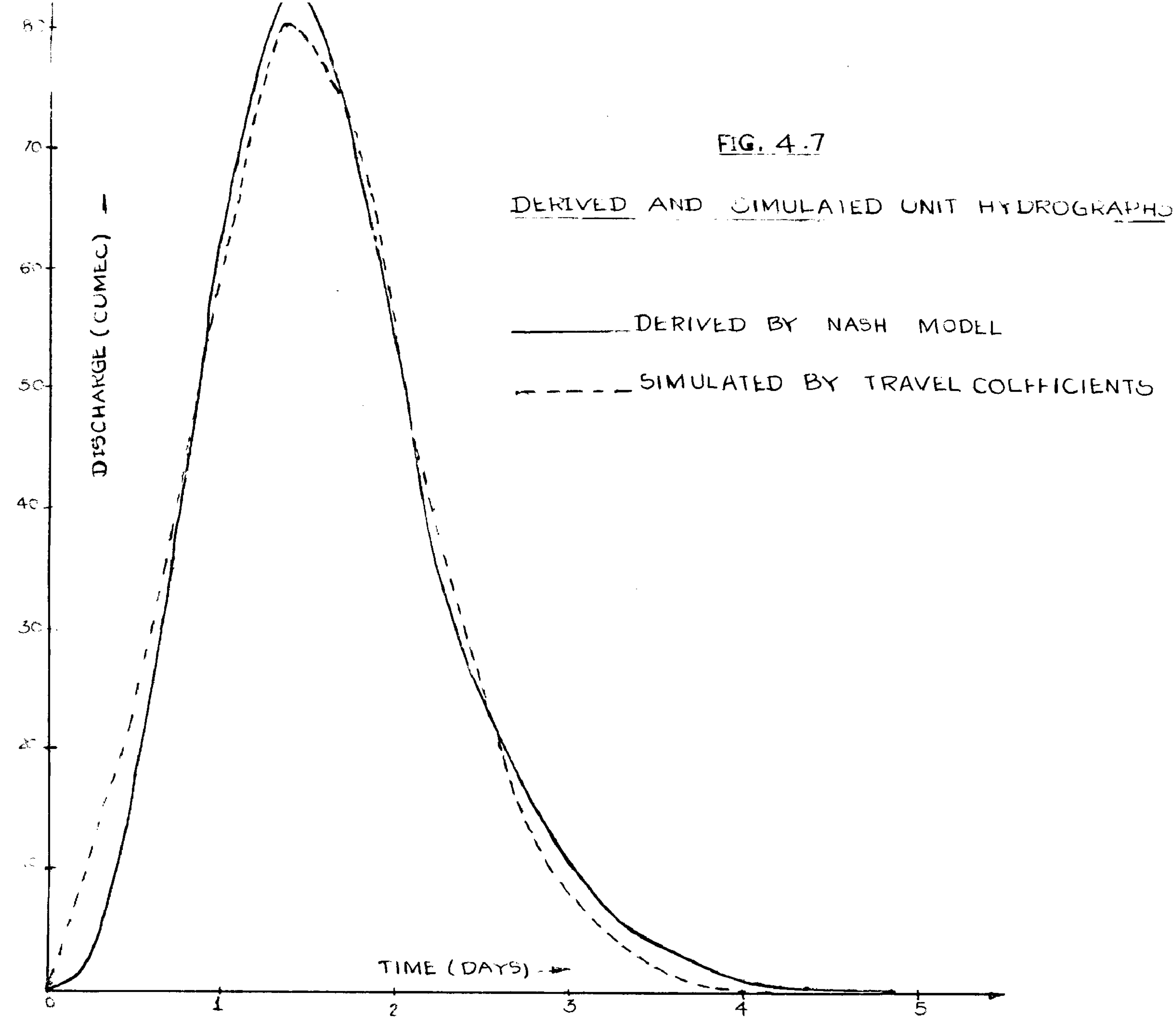


FIG. 4.7

DERIVED AND SIMULATED UNIT HYDROGRAPHS

Table 4.15

Fitting of Unit Hydrograph

Trial No.	Values of r Area 1	Area 2	Area 3	Area 4	Efficiency
1	0.60	0.60	0.80	0.95	98.87
2	0.60	0.60	0.80	0.85	98.66
3	0.60	0.60	0.85	0.95	99.04
4	0.60	0.60	0.85	0.85	98.93
5	0.60	0.65	0.85	0.95	98.76
6	0.60	0.65	0.75	0.85	98.67
7	0.50	0.60	0.80	0.95	98.38
8	0.55	0.60	0.80	0.85	97.90
9	0.55	0.60	0.85	0.95	98.80
10	0.60	0.60	0.80	0.90	98.78

4.6.4. Model for daily rainfall excess

The proposed model for daily rainfall excess has already been discussed in section 3.2.2.1. Accordingly data obtained for several storms in the historic record were analyzed by the technique of stepwise multiple regression. Some of the initial results obtained are given below.

(1) Multiple linear regression

Runoff coefficient (R.O.C.) = 0.24505 −0.006202x RAINFALL + 0.02075 x API

Multiple correlation coefficient = 0.65145

(2) Multiple linear regression with log transformed data

$$R.O.C. = \frac{API}{5.87192 (RAINFALL)^{0.14933}}$$

Multiple correlation coefficient = 0.60736

In order to improve this relations further it was decided to include two other variables. They were the duration of the storm and week number. In this study the week number has been assumed to commence from 20th May (i.e. week No.1 for May 20, to May 27 and so on) since only the monsoon period is considered although the practice is to count from Ist January. The results obtained are shown below.

(3) Multiple linear regression

$$R.O.C. = 0.164305 - 0.0076598 \times RAINFALL + 0.0132717 \times API + 0.002438 \times DURATION + 0.0225578 \times WEEK\ NUMBER$$

Multiple correlation coefficient = 0.7125

(4) Multiple linear regression with log transformed data

$$R.O.C. = \frac{0.10099\ API^{0.3255}\ DURATION^{0.1383}\ WEEK\ No.^{0.4103}}{RAINFALL^{0.2371}}$$

Multiple correlation coefficient = 0.662868

On the basis of highest multiple correlation coefficient the third relationship was accepted to be included in the rainfall runoff model. However, due to some other unknown factors which could not be considered in developing this relationship the observed and computed rainfall excess volumes could not be matched which is essential in any rainfall runoff model. In order to satisfy this requirement the runoff coefficient computed by the above relationship was modified by multiplying with a volume factor K.

4.6.5. Computer model for simulation of daily direct runoff during monsoon season

A computer program was developed to caliberate and test the proposed rainfall runoff model. Several factors have been made as the parameters of the model in order to limit the number of variables which have to be assumed. A particular method of optimization was not used but it was done through random sampling. The following parameters may be optimized by this computer program.

1. The initial travel coefficients for all four subareas
2. Pattern of rainfall within the day

The best combination of initial travel coefficients were determined in the following manner. The routine starts with the computation of daily direct runoff for the entire monsoon season selected in this study for the given initial travel coefficients and compares with observed daily direct runoff by calculating efficiency. Then the initial travel coefficient for the fourth subarea is varied in a particular range with the help of given increments and the best value of travel coefficient for this subarea is chosen on the basis of maximum efficiency.

Throughout this optimization the initial travel coefficients for other three sub areas remain constant at their given values. With the best value of coefficient for fourth area the same procedure is followed for third area, and so on In this manner the program finally decides the best combination of initial travel coefficients, which yields the maximum efficiency.

The distribution of rainfall within the day is varied by assuming different percentages of daily rainfall during 3 eight hourly periods within the day. The same routine for travel coefficients may be repeated for different combinations of percentages of daily rainfall for 3 eight hour periods. In this manner the best percentage distribution of rainfall within the day may be chosen.

Before going into optimization routine computer program works out the value of the volume factor K in daily rainfall excess model by matching seasonal volumes of observed and computed rainfall excess.

The computer program was run with the daily rainfall runoff data of 1972 and satisfactory results were obtained. The results may be summarized as follows.

Percentage distribution (assumed to be constant throughout)

First eight hours	33.333
Second eight hours	33.333
Third eight hours	33.333

Maximum efficiency achieved = 50.505%

The best combination of initial travel coefficients

Subarea	1	0.55
	2	0.55
	3	0.75
	4	0.92

The value of volume factor K in the daily rainfall excess model = 0.53051

The same data were analyzed for different percentage distributions. The results obtained are shown in Table 4.16.

Table 4.16

Trial No.	Percentage distribution Eight hour internal			Maximum Efficiency	Best set of travel coefficients. Subarea			
	1	2	3		1	2	3	4
1	70	20	10	47.621	0.55	0.55	0.75	0.92
2	40	40	20	47.643	0.55	0.60	0.85	0.95

On the basis of above results the following values for the parameters were chosen for further analysis.

Percentage distribution

First eight hour	33.333
Second eight hour	33.333
Third eight hour	33.333

Initial travel coefficients

Sub area	1	0.55
	2	0.55
	3	0.75
	4	0.92

The rainfall runoff model was tested with the independent data of 1970 for monsoon season in order to verify the reliability of model parameters derived with data of 1972. The results obtained for this data are summarized in table 4.17.

Table 4.17

Trial No.	Percentage Distribution Eight hour interval			Maximum Efficiency	Best set of travel co-efficients Sub- area			
	1	2	3		1	2	3	4
1	33.333	33.333	33.333	74.203	0.55	0.55	0.75	0.92
2	70.000	20.000	10.000	72.061	0.55	0.60	0.85	0.95

The value of volume factor K in daily rainfall excess model = 0.69772

It may be seen that the parameter values decided on the basis of 1972 data have not changed in the case of maximum efficiency, for 1970 data.(Trial No.1). Only the factor K has changed slightly.

The plotter available with IBM 360/44 computer was used to plot the observed and simulated direct runoff hydrographs for 1970 data. The plotted hydrographs are shown in figure 4.8.

The performance of the model with the new value of factor K obtained for 1970 data was also checked with the date of 1972. The observed and simulated hydrographs obtained here are shown in figure 4.9.It is seen from this figure that the matching of observed and simulated hydrographs is fairly satisfactory, particularly in view of only one season data being used for model caliberation. This result will improve further if more data

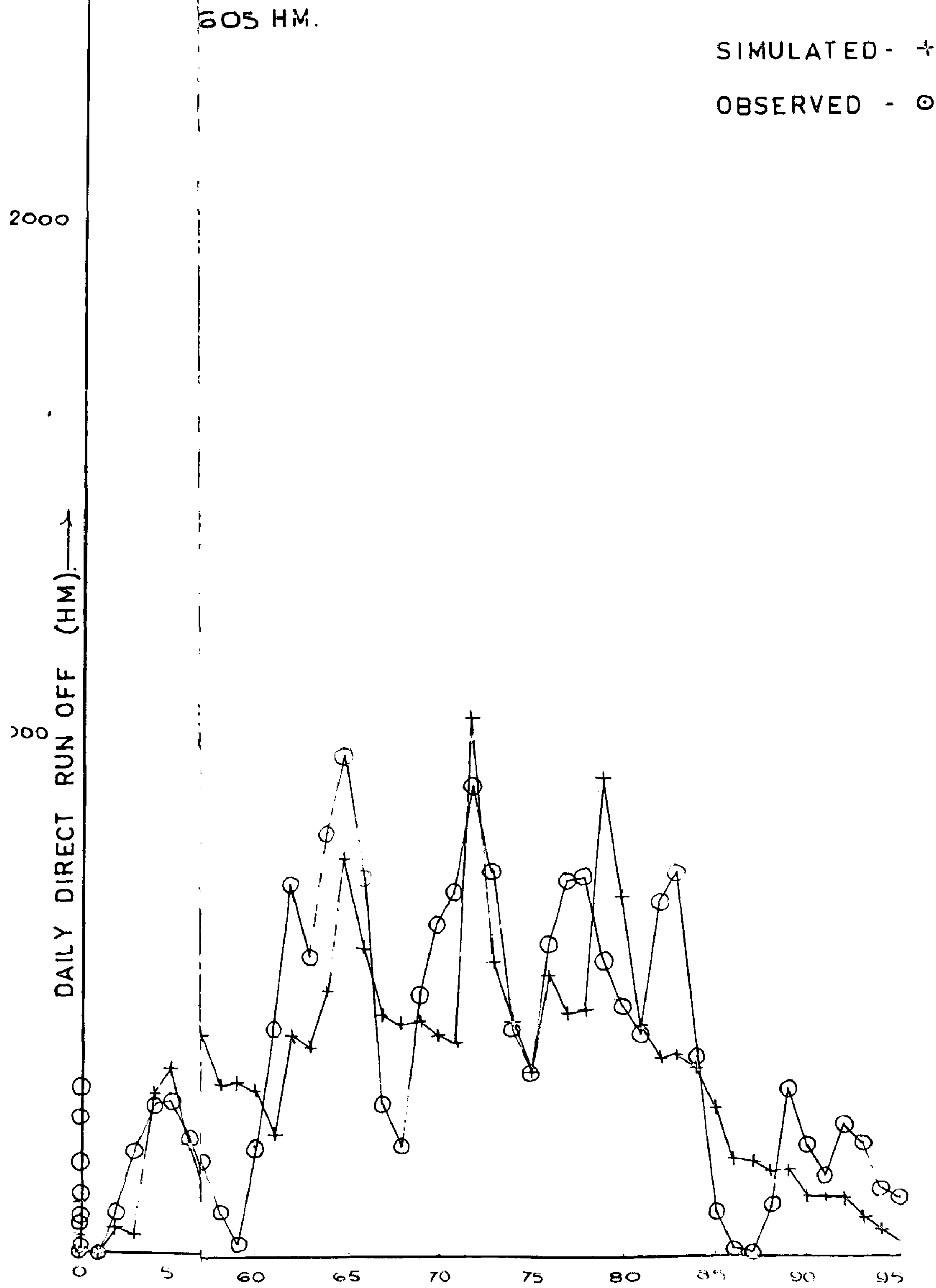


FIG:- 4·8 :- GRAPHS FOR THE PERIOD

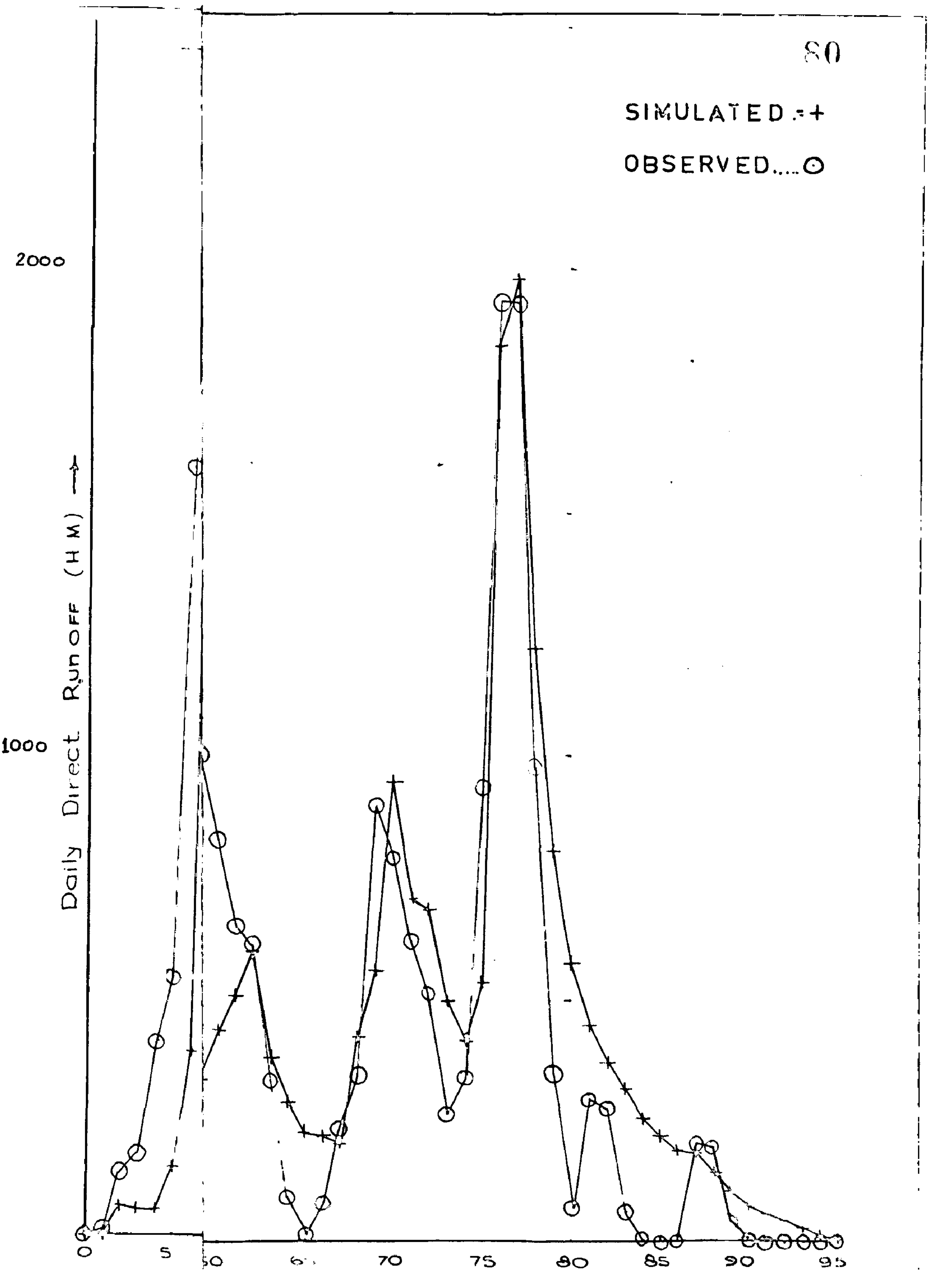


FIG. 4.9 FOR THE PERIOD

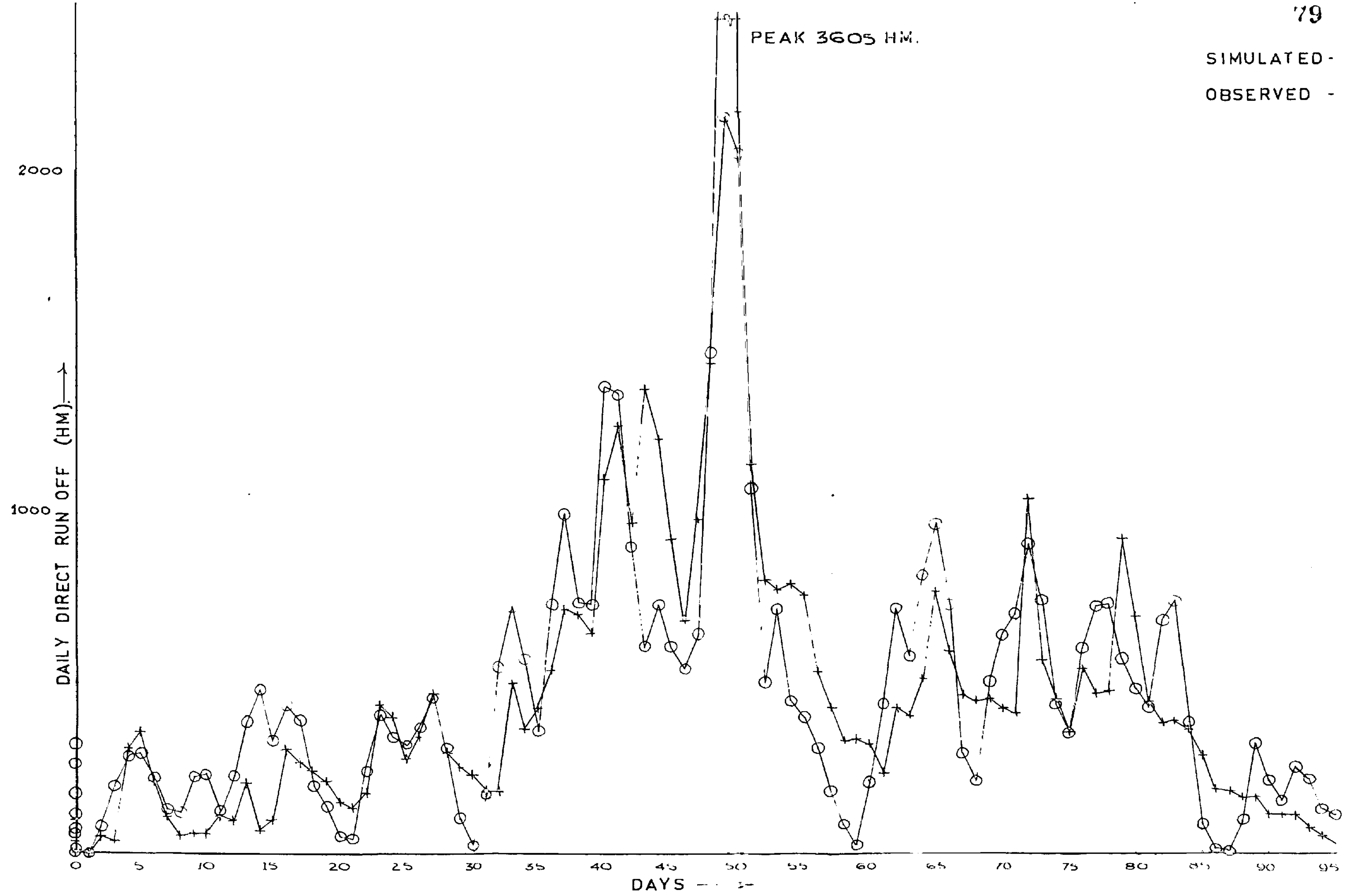


FIG:- 4.8 :- OBSERVED AND SIMULATED DAILY DIRECT RUN OFF HYDROGRAPHS FOR THE PERIOD JULY, 1 TO OCTOBER, 3, 1972.

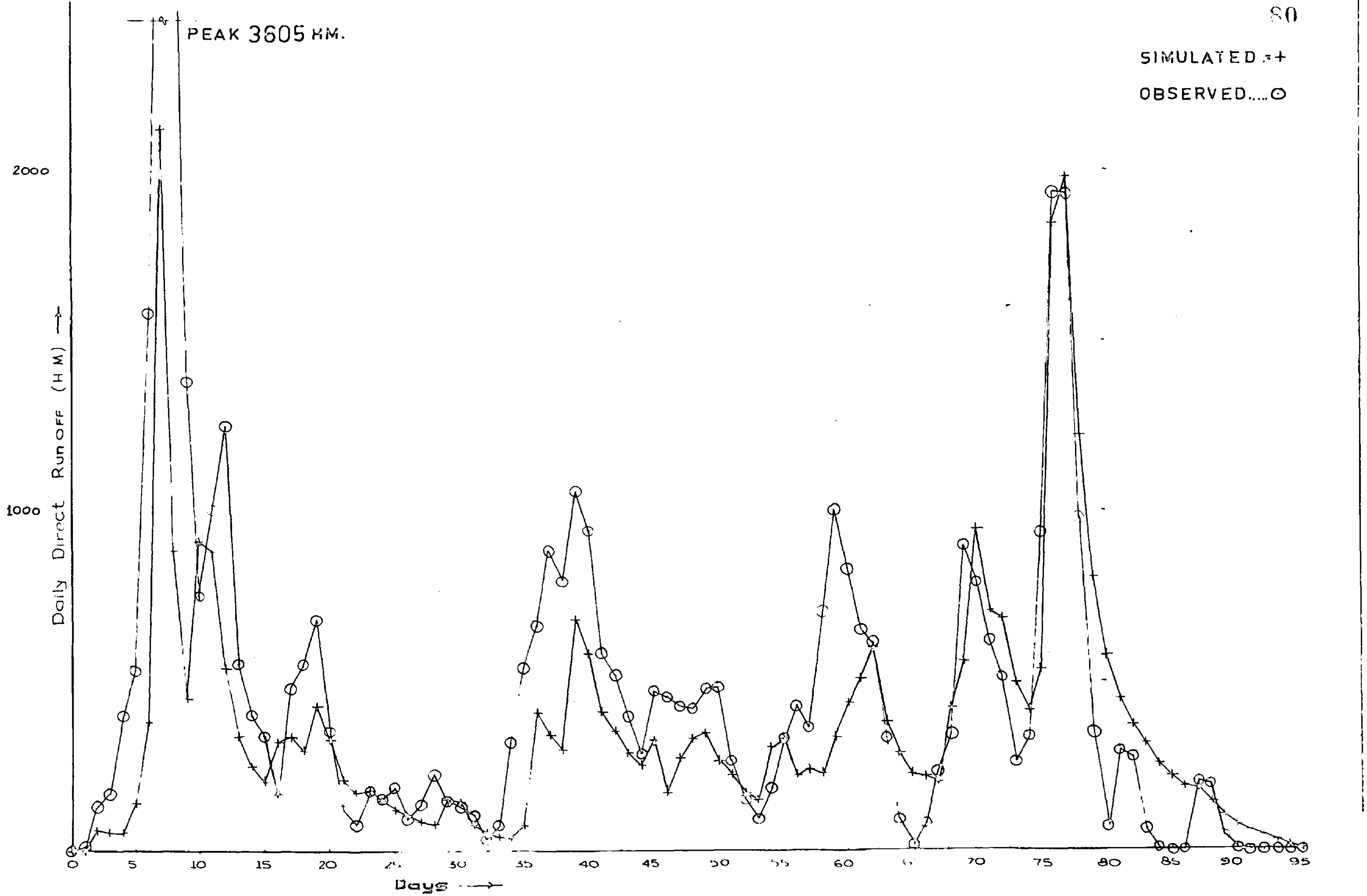


FIG. 4. 9.- OBSERVED AND SIMULATED DIRECT RUN OFF HYDROGRAPHS FOR THE PERIOD JUNE 25 TO SEPTEMBER 27, 1970.

(say 10 years monsoon seasons) is used for evaluating model parameters though it will involve more computer time.

4.7. APPLICATION OF STOCHASTIC DAILY STREAMFLOW MODEL TO GENERATE SYNTHETIC SEQUENCES OF DAILY STREAMFLOW

The stochastic daily rainfall model and the daily rainfall runoff model were combined to yield the proposed stochastic daily streamflow model. This was done simply by adding a subroutine to the stochastic daily rainfall model to convert the generated daily rainfall to daily runoff using the model caliberated with observed data.

The model generates daily streamflow for the period 20th June to 17th September by transforming the daily rainfall generated for the same period through rainfall runoff model. Only three raingauges are involved in computing average rainfall over each subarea since the daily rainfall is generated only at three rain gauge stations. Provision has been made in the program to compute both API and week number which inturn will be used to compute daily values of runoff coefficient.

The baseflow component of daily streamflow is obtained from a curve of direct runoff versus baseflow as described in section 3.3.2.2. This curve has been developed from the runoff hydrographs at the end of monsoon season by isolating the storms at the end of monsoon season and employing normal recession curve and baseflow recession curve to obtain direct runoff and baseflow seperately. The curve was included in the computer model in the form of a series of straight lines approximating the curve.

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The performance of the stochastic daily streamflow model was investigated by generating stochastic daily runoff for a period of six years with the initial API values same as that of the observed six years record. The statistics of direct daily runoff in 1970,1972 and generated direct daily runoff have been listed in Table 4.18.

Table 4.18

Statistics of observed and generated daily direct runoff

Observed data (Monsoon season)

Year	Mean (H.M.)	Standard deviation
1970	465.924	486.720
1972	363.184	376.628

Generated Data

Ninety day monsoon period	Mean (H.M.)	Standard deviation
1	374.839	285.012
2	295.012	284.052
3	482.952	517.992
4	502.733	590.131
5	388.935	372.813
6	344.076	370.632

The observed and generated values of seasonal runoff (baseflow included) volumes have been listed in Table 4.19.

Table 4.19

Observed and generated seasonal runoff volumes

Observed (June 20 to Sept.17)		Generated (June 20 to Sept. 17)	
Year	Runoff Vol.(H.M.)	Year	Runoff Vol.(H.M.)
1970	60719.9	1	39566.4
1971	99818.3	2	31140.2
1972	39914.1	3	50854.5
1973	124783.8	4	52871.1
1974	51588.8	5	41054.2
1975	56515.9	6	36297.0

The mean and standard deviation for observed and generated seasonal volumes are as follows.

	Mean (HM)	Standard deviation (HM)
1. Generated	41964.0	7679.6
2. Observed	72223.5	29924.3

It may be seen from the above results, although the model is able to reproduce direct daily runoff values fairly accurately, observed and generated seasonal volumes are very different in their statistics. This is due to the fact that the baseflow curve is not able to reproduce baseflow component accurately. This becomes further clear when the observed and reproduced baseflow volumes are considered.

Observed baseflow volume for 1970 = 14127 HM

Maximum of base flow volumes reproduced = 5112.0 HM

However this difference could have been reduced further had the baseflow model been developed from adequate runoff data.

CHAPTER-5

DISCUSSION OF RESULTS, CONCLUSIONS AND SUGGESTIONS FOR FURTHER STUDIES

5.1. INTRODUCTION

A stochastic daily streamflow model was proposed to generate synthetic sequences of daily streamflow and the same was tested with the limited data of Naula catchment of Ramganga basin. The stochastic streamflow model comprised of two separate models; a stochastic multi-station daily rainfall generator and deterministic daily rainfall runoff model developed on the basis of division of catchment into isochrones and using travel coefficients to account for the natural transformation of discharge along the length of the river. The results obtained (as given in Chapter 4) are quite encouraging in spite of the limited data used for this study. The discussions of the results and conclusions have been given in following sections.

5.2. PERFORMANCE OF THE MODELS

The results obtained in this study have been analyzed in two stages as follows -

1. Performance of stochastic multi-station daily rainfall model
2. Performance of stochastic daily streamflow model

5.2.1. Performance of Stochastic daily rainfall model

The analysis of results obtained at different stages of the calibration of model and its application in data generation are given below.

1. Calibration of the model

(a) In order to choose statistically homogeneous periods or seasons within the year, the five day average rainfall evaluated from all six years of rainfall data Choukhutia was plotted against the months (Fig.4.2). This plot clearly defined the high rainfall period from June 20 to September 17, which was subsequently used for further analysis.

(b) The model has been designed to generate rainfall sequences only at three rain gauge stations in order to limit the large number of combinations of wet-dry probabilities possible. However, the catchment selected had six raingauge stations. The best combination of rain gauge stations which could adequately define the average rainfall over the catchment was selected for the rainfall model, as described in section 4.4.2. The three raingauge stations selected were Choukhutia (A), Gairsain (B) and Tamadhawn (C).

(c) In some cases the probability of a wet day following a wet day is greater if the previous day had a high precipitation that if the previous day's precipitation had been light. To account for this effect the wet-dry probabilities were divided into three levels depending upon the rainfall amount of the previous day at station A, B or C. Since the data was limited to six year period only, three levels were chosen. Large number of levels with limited data would make transition probabilities unrepresentative. Boundary values of the levels were selected on the basis of a plot of transition probability of a wet day following a wet day versus different rainfall amounts on previous day (Fig.4.5). This plot was used to decide about the boundary values for the three levels as 0.025, 1.5 and 5.5.

(d) The transition probabilities evaluated for different combinations of wet-dry states could not be properly evaluated for some cases on account of the limited data used to calibrate the model. As it could be seen from tables 4.4, 4.5 and 4.6 some of the cases have only a few events involved in computing wet-dry probabilities. For example, the level 3, case 4 of station A had only 2 values of wet day following wet day and zero values of dry day following a wet day and hence the transition probability computed was 1.00 which is extremely high.

(e) The regression relations were developed for all three levels of four cases (1,2,5 and 6) of station B and six cases (1,2,3,5,6 and 7) of station C. (Tables 4.9 and 4.10). The correlation among rain gauge stations in some of the cases was not satisfactory due to limited data being used as indicated by low values of correlation coefficients. This was mainly due to limited number of values involved in developing regression relations for those particular cases. However, in some other cases reasonably good relationships were established.

(f) The conditional cumulative distributions derived from the limited data were somewhat approximate, since the number of events involved in individual classes were less. The effect of this is more pronounced in the case of station C (Tables 4.7 and 4.8).

2. Generation of Synthetic sequences

Two cases have been considered while generating synthetic sequences of daily rainfall of 5, 25, and 100 years. In the first case the generation of daily rainfall is achieved mainly through interstation regression relations whereas in the second case it was done by sampling from historic cumulative frequency curves.

In both the cases the results obtained are quite encouraging inspite of the limited data being used. The mean season rainfall and standard deviation of mean season rainfall are of the same order of magnitude as those of observed sequence (Tables 4.12, 4.13). However, the mean season rainfall of generated sequences is somewhat less than that of observed sequence. For example, the mean season rainfall at first station on the basis of 5 year generated sequence was 96.57 cms. in the first case above, whereas the same for the observed sequence was 108.36. This effect was observed in both the cases. However, the first case was better in reproducing mean season rainfall as compared to second case. Standard deviation of mean season rainfall was generally lower in comparison to that of observed sequence. This is possibly due to the assumption of homogeneous season.

5.2.2. Performance of Stochastic daily streamflow model

The stochastic daily streamflow model comprised of two separate component models i.e. stochastic daily rainfall model and the daily rainfall-runoff model. The performance of stochastic daily rainfall model has been discussed above. The discussion on the results obtained for the rainfall - runoff model and the combined daily streamflow model is given below.

1. Calibration of the model

(a) A reliable estimate of basin travel time was difficult to obtain since the available data was limited. It was approximated to be the product of n and K in the Nash model. On this basis, it was computed as 32 hours for the Naula catchment. Although the travel time was made a model parameter to be optimized, it could not be tried due to lack of computer time available.

(b) The available data do not indicate any clue about the variation of rainfall within the day. For this reason, it was necessary to assume some distribution of rainfall within the day. In this study various percentage distribution at 8 hourly intervals were tried and the best percentage distribution on the basis of maximum efficiency was chosen for further analysis. The adopted distribution, however, assumes that rain occured throughout the day, a fact which is not true for all the days in the record. However, the differences in final results for various percentage distribution patterns were marginal. Improved results could be obtained by deriving some empirical distribution for variation of rainfall within the day from recording raingauge data of some typical storms. For the present study this could not be done as they were not available.

c) The model for daily rainfall excess was derived from the values of runoff coefficient obtained for some typical storms of six years monsoon data, by relating them to some other appropriate parameters such as API, Rainfall etc., using stepwise multiple regression technique. A volume factor K was introduced in this relation as a model parameter and the same was evaluated by matching the observed and computed rainfall excess volumes. As it is seen from the results obtained in section 4.6.5. the value of this volume factor K was almost the same for both the years of data used for model calibration.

(d) On the basis of a previous study conducted for base flow separation (Linseley et.al., 1949) the baseflow was related to direct runoff by analyzing some typical hydrographs in the observed record. This model for baseflow, however, could only approximately reproduce the baseflow volumes. Better definition of baseflow component requires additional data regarding soil moisture and evaporation, which was not available for the present study.

In spite of many difficulties and assumptions involved, the simulation model for daily rainfall and runoff gave satisfactory results. The model was able to simulate the daily direct runoff for monsoon season in 1972 satisfactorily, with an efficiency of about 50 percent. The efficiency of 74 percent obtained by using 1970 was still better. The results could be improved further if the model parameters are evaluated on the basis of entire observed record which includes both high and low flow years. However, this will require more computer time.

2. Generation of Synthetic sequence

The daily streamflow was generated for monsoon seasons of only six years, on account of limited computer time available. The statistics of generated sequence of daily direct run-off compares well with that of observed sequence as evident from table 4.18. Although the values of Mean and standard deviation were varying from year to year the order of magnitude remained same as that of observed sequence. Still better results could be obtained by using all six years of data for parameter estimation.

The seasonal runoff volumes (base flow included) could not be reproduced satisfactorily. This seems to be mainly due to the inadequacy of data required in predicting the baseflow component. Other reasons for this difference might be the carry-over effect of the inadequacies in the daily rainfall model and the assumption involved in the rainfall runoff model.

5.3. CONCLUSIONS

Main conclusions, that have been drawn from the present study are given seperately for the two models as follows.

5.3.1. Stochastic multi-station rainfall model

(a) Six years data seems to be sufficient to indicate clearly the satistically homogeneous periods. However, the periods before and after monsoon period would be indicated still better if longer data record is used.

(b) The generation of rainfall at three stations may not be adequate for larger catchments. It has been found in a recent study (Johanson, 1971) that for modelling purposes three rainfall gauges over a 1,000 square mile area are adequate for streamflow volume simulation. However, the number of rain gauges required are more even when the area is small, if the variation of topography is high within the catchment.

(c) Short record of rainfall such as that used for the present study is not completely adequate to indicate clearly the levels of rain to be used. The use of longer records in deciding levels would further improve the model performance.

(d) Longer rainfall records should be used to obtain reliable values of transition probabilities, regression relations among stations and cumulative frequency distributions. This is in agreement with the observations by Kraeger (1971) who suggested that about thirty years of precipitation data are needed for adequate definition of model parameters.

(e) In spite of the limited data used for the present study the performance of the stochastic multi-station rainfall model is satisfactory. However, the standard deviation of generated mean season rainfall was somewhat low when compared to that of observed on account of the assumption of homogeneous season. This is because, the model combines rare intense storms and general storms in the same season and therefore the generated sequences have a tendency to exhibit low variability.

5.3.2. Daily Rainfall Runoff Model

(a) The use of limited data does not permit the reliable estimation of basin travel time. In absence of adequate data the basin travel time should be made a parameter to be optimized by using a suitable optimization routine.

(b) Wherever possible, recording raingauge data should be obtained at least for some typical storms in order to derive some empirical variation of rainfall within the day. The use of such empirical distribution would improve the performance of the model.

(c) The model for rainfall excess should be calibrated on the basis of daily values of rainfall excess, obtained after seperation of complex hydrographs into simple hydrographs corresponding to daily rainfall values. The parameters of this model must be decided on the basis of sample record which include low as well as high streamflow years.

(d) The model proposed for baseflow component could be revised further with a water balance type of model which include soil moisture and evaporation as parameters. However this will require evaporation and soil moisture data and would involve more computer time in calibration of the model.

5.4 SUGGESTIONS FOR FURTHER STUDIES

In the light of the results obtained in this study, the following suggestions are given for further studies.

(1) Since the length of the record of rainfall data required for adequate definition of rainfall model parameters depends upon the climatic conditions of the region, the parameter stability should be checked by evaluating the parameter values for data records of different lengths for different catchments of varying sizes. By doing so, one can arrive at a record length which is the minimum required to define model parameters in a particular region.

(2) Further studies should be carried out with some empirical distribution for hourly distribution of daily rainfall. This may be obtained from recording raingauge data for a few storms in the area.

(3) The parameters of rainfall runoff model must be evaluated on the basis of entire record in order to arrive at more reliable values. The parameters evaluated by data of a low flow year may not reproduce runoff during a year of highflow. The optimization of parameters must be carried out using some suitable optimization technique.

4. Further studies must be carried out with a revised model for baseflow component, possibly taking more parameters such as soil moisture and evaporation into account. The parameters should be such that the model adequately accounts for the progressive increase of baseflow component with the onset of monsoon.

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APPENDIX

COMPUTER PROGRAMS

The computer programs developed for the present study and their salient features are as follows :-

1. Program for 'WET-DRY PROBABILITIES FOR FIRST STATION (A)'

This program computes the probability of wet day following a wet day at first station (A) for different wet dry states. It also determines the cumulative frequency distribution at first station. The input data include boundary values for levels of rain, class intervals for cumulative distribution, and rainfall data at all three stations for each year. The program outputs probability of wet day following a wet day for each level of rain and wet dry states. The output also includes the cumulative number of values falling in each class of the cumulative frequency distribution.

2. Program for 'WET-DRY PROBABILITIES AND CONDITIONAL CUMULATIVE DISTRIBUTION FOR SECOND STATION (B)'

The probability of wet day following a wet day is evaluated for each level of rain and combination of wet dry states in a manner similar to that of first station. The observed record of rainfall is scanned and the values falling in each class are accumulated at different storage locations. The program also outputs the cumulative number of values falling in each class of the conditional cumulative frequency distribution. The rainfall values to be used in deriving regression relations are also punched out.

3. Program for 'WET-DRY PROBABILITIES AND CONDITIONAL CUMULATIVE DISTRIBUTION FOR THIRD STATION(C)'

This program was developed to compute the probability of wet-day following a wet day at third station (C). Apart from this the output consists of rainfall values to be used for different regression relations and the number of events falling in each class interval of the conditional cumulative frequency distribution.

4. Program for 'OBSERVED CUMULATIVE FREQUENCY DISTRIBUTIONS FOR ALL STATIONS'

This program evaluates the number of events falling in each class of the observed frequency distribution at each station and outputs in a cumulative form.

5. Program for 'BIVARIATE CORRELATION ANALYSIS FOR ORDINARY AND TRANSFORMED DATA'

The slope and the intercept of the regression relation for each case of level of rain and wet dry state are evaluated for ordinary data. The rainfall values are then transformed from observed cumulative frequency distribution to a cumulative normal distribution. The parameters of the regression relations are evaluated for the transformed data also.

6. <u>Program for 'TRANSFORMATION TO 'NORMAL' FOR MULTI-VARIATE CASES'</u>

This is a simple program to transform the rainfall values to be used in multiple regression relations into a cumulative normal distribution. The observed cumulative frequency curves and cumulative normal frequency curve are fed in the form of series of straight lines assuming the curves.

7. <u>Program for 'DAILY RAINFALL RUNOFF MODEL'</u>

This is the optimization program to evaluate the parameters of daily rainfall runoff model. The computations are commenced with the evaluation of week number for different days which will be used later to compute run-off coefficient. The average rainfall over each sub-area as well as over entire area is computed and the same is used to compute API. These computed parameter values are then used to evaluate runoff coefficients for each day. The program then computes the travel coefficients for each subarea on each day and subsequently all rainfall values are transformed to daily runoff values. The efficiency is then computed which is compared with the previous maximum efficiency achieved and proceeds for the next iteration. Finally program outputs the best combination of travel coefficients and the maximum efficiency achieved for different combinations of percentage distribution. A complete simulation run with two different percentage distributions took only 5 minutes and 28 seconds in the IBM 360/44 computer.

8. Program for 'STOCHASTIC DAILY STREAMFLOW MODEL'

This is the complete computer model to generate synthetic sequences of daily streamflow values. The program first generates the daily rainfall for the period of record required with the help of transition probabilities and regression relations developed by other programs. Then the generated rainfall data are transformed to daily streamflow data through the daily rainfall runoff model with the optimized parameters. This program uses several subroutines. Subroutine 'GENERA' is to generate daily rainfall values at 3 stations and subroutine 'WRTOUT' prints out the generated data to any desired length. However, this is optional. Subroutine 'TRANSF' transforms the rainfall values into cumulative normal distribution, whereas 'SFNART' transforms back from the cumulative normal distribution. Subroutine RANDUM generates rectangularly distributed random numbers whereas subroutine 'GAUSSB' converts these random numbers into 'normal' by central limit theorem. The model was able to generate 100 years of daily rainfall data for monsoon season in 5 minutes and 7 seconds in the IBM 360/44 computer. For the generation of 6 years of daily streamflow the model took 5 minutes and 50 seconds.

```
C      WET-DRY PROBABILITIES FOR STATION A BY J.T.B.OBEYSEKERA
C      RAINFALL AT STATION I ON THE DAY J IS A(I,J)
C      LEVELS O F RAIN = RLEV(N)
       DIMENSION RLEV(5),A(3,370),IW(8,5),ID(8,5),RL(15),ICL(15)
       DIMENSION PROB(8,5)
C      PROBABILITIES OF HISTORIC DATA(FOR FIRST STATION)
C      READ INPUT DATA
       READ 200,NDATA,NY,NL,KL
 200   FORMAT(5I5)
       READ 199,(RLEV(N),N=1,NL)
 199   FORMAT(8F10.3)
       READ 198,(RL(N),N=1,KL)
 198   FORMAT(16F5.2)
       DO 203 M=1,8
       DO 203 N=1,NL
       IW(M,N)=0
 203   ID(M,N)=0
       DO 204 N=1,KL
 204   ICL(N)=0
       READ 207, X
 207   FORMAT(F5.3)
       DO 210 IJ=1,NY
       DO 206 I=1,3
       READ 205,(A(I,J),J=1,NDATA)
 205   FORMAT(16F5.3)
 206   CONTINUE
C      COUNT DAILY RAINFALL EVENTS IN EACH CLASS
       DO 52 J=2,NDATA
       IF(A(2,J-1)-X) 1,1,2
   2   IF(A(3,J-1)-X) 3,3,4
  4    IF(A(1,J-1)-X) 5,5,6
  3    IF(A(1,J-1)-X) 7,7,8
  1    IF(A(3,J-1)-X)  9,9,10
  10   IF(A(1,J-1)-X) 11,11,12
   9   IF(A(1,J-1)-X) 121,121,13
C      CASE SELECTION
C      CASE-1-WET-WET-WET
   6   M=1
       Z=A(1,J-1)
       GO TO 50
C      CASE 5 -WET- WET- DRY
   5   M=5
       Z=A(2,J-1)
       GO TO 50
C      CASE 2 -WET- DRY- WET
  8    M=2
       Z=A(1,J-1)
       GO TO 50
C      CASE - 6 - WET - DRY - DRY
  7    M=6
       Z=A(2,J-1)
       GO TO 50
C      CASE 3 - DRY - WET - WET
  12   M=3
       Z=A(1,J-1)
```

```
      GO TO 50
C     CASE 7 - DRY - WET - DRY
   11 M=7
      Z=A(3,J-1)
      GO TO 50
C     CASE 4- DRY - DRY - WET
   13 M=4
      Z=A(1,J-1)
      GO TO 50
C     CASE 8 - DRY - DRY - DRY
  121 M=8
      IF(A(1,J)-X) 14,14,15
   14 ID(M,1)=ID(M,1)+1
      GO TO 52
   15 IW(M,1)=IW(M,1)+1
      GO TO 52
   50 CONTINUE
      DO 51 L=1,NL
      N=NL+1-L
      IF(Z-RLEV(N)) 51,51,17
   17 IF(A(1,J)-X) 18,18,19
   19 IW(M,N)=IW(M,N)+1
      GO TO 52
   18 ID(M,N)=ID(M,N)+1
      GO TO 52
   51 CONTINUE
   52 CONTINUE
C     OBSERVED CUMULATIVE RAINFALL FREQUENCY AT STATION  A
      DO 140 J=1,NDATA
      DO 141 L=1,KL
      N=KL+1-L
      IF(A(1,J)-RL(N)) 141,143,143
  143 ICL(N)=ICL(N)+1
      GO TO 140
  141 CONTINUE
  140 CONTINUE
  210 CONTINUE
      DO 144 N=2,KL
      ICL(N)=ICL(N)+ICL(N-1)
  144 CONTINUE
      DO 53 M=1,7
      DO 53 N=1,NL
      IF(IW(M,N)) 170,170,171
  170 IF(ID(M,N)) 172,172,171
  172 ID(M,N)=9999
  171 CONTINUE
      FW=IW(M,N)
      FD=ID(M,N)
   53 PROB(M,N)=FW/(FW+FD)
      IF(IW(8,1)) 173,173,174
  173 IF(ID(8,1)) 175,175,174
```

```
175   ID(8,1)=9999
174   CONTINUE
      FW=IW(8,1)
      FD=ID(8,1)
      PROB(8,1)=FW/(FW+FD)
      DO 54 M=1,7
      DO 54 N=1,NL
      PUNCH 100,M,N,IW(M,N),ID(M,N),PROB(M,N)
100   FORMAT(10X,2I5,2(10X,I5),F10.3)
 54   CONTINUE
      M=8
      N=1
      PUNCH 100,M,N,IW(M,N),ID(M,N),PROB(M,N)
      DO 145 N=1,KL
      PUNCH 146,N,ICL(N)
146   FORMAT(10X,I5,10X,I5)
 145  CONTINUE
      STOP
      END


C     WET-DRY PROBABILITIES AND CONDITIONAL CUMULATIVE
C     DISTRIBUTION FOR SECOND STATION (B) - J.T.B.OBEYSEKERA
      DIMENSION A(3,100),RLEV(5),RLB(15),IW(8,4),ID(8,4),ICB(15)
      DIMENSION PROB(8,4),RB(200),RB1(3,80),RB2(3,80),RB5(3,80)
      DIMENSION RB6(3,80),RA1(3,80),RA2(3,80),RA5(3,80),RA6(3,80)
      READ 500,NDATA,NY,NL,KLB
500   FORMAT(5I5)
      READ 501,(RLEV(N),N=1,NL)
501   FORMAT(8F10.3)
      READ 502,(RLB(N),N=1,KLB)
502   FORMAT(16F5.2)
      DO 503 MM=1,8
      DO 503 NN=1,NL
      IW(MM,NN)=0
503   ID(MM,NN)=0
      DO 504 NN=1,KLB
504   ICB(NN)=0
      K=0
      READ 499,X
499   FORMAT(F5.3)
      DO 510 IJ=1,NY
      DO 506 I=1,3
      READ 505,(A(I,J),J=1,NDATA)
505   FORMAT(16F5.3)
506   CONTINUE
C     COUNT DAILY RAINFALL EVENT IN EACH CLASS
      DO 352  J=2,NDATA
      IF(A(1,J)-X) 301,301,302
302   IF(A(3,J-1)-X) 303,303,304
```

```
 304   IF(A(2,J-1)-X) 305,305,306
 303   IF(A(2,J-1)-X) 307,307,308
 301   IF(A(3,J-1)-X) 309,309,310
 310   IF(A(2,J-1)-X) 311,311,312
 309   IF(A(2,J-1)-X) 3121,3121,313
C      CASE SELECTION
 306   M=1
       Z=A(1,J)
       GO TO 350
 305   M=5
       Z=A(1,J)
       GO TO 350
 308   M=2
       Z=A(1,J)
       GO TO 350
 307   M=6
       Z=A(1,J)
       GO TO 350
 312   M=3
       Z=A(2,J-1)
       GO TO 350
 311   M=7
       Z=A(3,J-1)
       GO TO 350
 313   M=4
       Z=A(2,J-1)
       GO TO 350
3121   M=8
       IF(A(2,J)-X) 314,314,315
 314   ID(M,1)=ID(M,1)+1
       GO TO 352
 315   IW(M,1)=IW(M,1)+1
       K=K+1
       RB(K)=A(2,J)
       GO TO 352
 350   CONTINUE
       DO 351 L=1,NL
       N=NL+1-L
       IF(Z-RLEV(N)) 351,351,317
 317   IF(A(1,J)-X) 3000,3000,4000
4000   IF(A(2,J)-X) 318,318,319
 319   IW(M,N)=IW(M,N)+1
       IF(M-1) 3001,3002,3001
3002   KK=IW(M,N)
       RB1(N,KK)=A(2,J)
       RA1(N,KK)=A(1,J)
       GO TO 352
3001   IF(M-5) 3003,3004,3003
3004   KK=IW(M,N)
       RB5(N,KK)=A(2,J)
       RA5(N,KK)=A(1,J)
       GO TO 352
3003   IF(M-2) 3005,3006,3005
```

```
3006  KK=IW(M,N)
      RB2(N,KK)=A(2,J)
      RA2(N,KK)=A(1,J)
      GO TO 352
3005  IF(M-6) 3007,3008,3007
3007  GO TO 352
3008  KK=IW(M,N)
      RB6(N,KK)=A(2,J)
      RA6(N,KK)=A(1,J)
      GO TO 352
 318  ID(M,N)=ID(M,N)+1
      GO TO 352
3000  IF(A(2,J)-X) 3009,3009,3010
3010  IW(M,N)=IW(M,N)+1
      K=K+1
      RB(K)=A(2,J)
      GO TO 352
3009  ID(M,N)=ID(M,N)+1
      GO TO 352
 351  CONTINUE
 352  CONTINUE
 510  CONTINUE
C     CUMULATIVE FREQENCY (CONDITIONAL) AT B/NO RF AT A
      DO 440 J=1,K
      DO 441 L=1,KLB
      N=KLB+1-L
      IF(RB(J)-RLB(N)) 441,443,443
 443  ICB(N)=ICB(N)+1
      GO TO 440
 441  CONTINUE
 440  CONTINUE
      DO 444 N=2,KLB
      ICB(N)=ICB(N)+ICB(N-1)
 444  CONTINUE
C     COMPUTE PROBABILITIES OF RAIN AT B
      DO 353 M=1,7
      DO 353 N=1,NL
      IF(IW(M,N)) 370,370,371
 370  IF(ID(M,N))372,372,371
 372  ID(M,N)=1
 371  CONTINUE
      FW=IW(M,N)
      FD=ID(M,N)
 353  PROB(M,N)=FW/(FW+FD)
      IF(IW(8,1)) 373,373,374
 373  IF(ID(8,1)) 375,375,374
 375  ID(8,1)=1
 374  CONTINUE
      FW=IW(8,1)
      FD=ID(8,1)
      PROB(8,1)=FW/(FW+FD)
      DO 354 M=1,7
      DO 354 N=1,NL
      PUNCH 300, M,N,IW(M,N),ID(M,N),PROB(M,N)
 300  FORMAT(4(10X,I5),F8.4)
 354  CONTINUE
```

```
      M=8
      N=1
      PUNCH 300, M,N,IW(M,N),ID(M,N),PROB(M,N)
      DO 445 N=1,KLB
      PUNCH 446, N,ICB(N)
446   FORMAT(2(10X,I5))
445   CONTINUE
      M=1
      DO 699 N=1,NL
      KK=IW(M,N)
      IF(KK) 699,699,698
698   DO 700 K=1,KK
700   PUNCH 701,M,N,RA1(N,K),RB1(N,K)
701   FORMAT(2I5,2F10.3)
699   CONTINUE
      M=2
      DO 703 N=1,NL
      KK=IW(M,N)
      IF(KK) 703,703,697
697   DO 702 K=1,KK
702   PUNCH 701,M,N,RA2(N,K),RB2(N,K)
703   CONTINUE
      M=5
      DO 704 N=1,NL
      KK=IW(M,N)
      IF(KK) 704,704,696
696   DO 705 K=1,KK
705   PUNCH 701,M,N,RA5(N,K),RB5(N,K)
704   CONTINUE
      M=6
      DO 706 N=1,NL
      KK=IW(M,N)
      IF(KK) 706,706,695
695   DO 707 K=1,KK
707   PUNCH 701,M,N,RA6(N,K),RB6(N,K)
 706  CONTINUE
      STOP
      END
```

```
C     WET-DRY PROBABILITIES AND CONDITIONAL CUMULATIVE
C     DISTRIBUTION FOR THIRD STATION (C) J.T.B.OBEYSEKERA
      DIMENSION A(3,100),RLEV(4),RLC(15),IW(8,4),MW(8,4),ID(8,4),IC(15)
      DIMENSION RC(50),B1(3,30),A1(3,30),C1(3,30),B5(3,30),A5(3,30)
      DIMENSION C5(3,30),A2(3,30),C2(3,30),A6(3,30),C6(3,30),B3(3,30)
      DIMENSION C3(3,30),B7(3,30),C7(3,30)
      READ 500,NDATA,NY,NL,KLC
  500 FORMAT(16I5)
      READ 501,(RLEV(N),N=1,NL)
  501 FORMAT(8F10.3)
      READ 502,(RLC(N),N=1,KLC)
  502 FORMAT(16F5.3)
      DO 503 M=1,8
      DO 503 N=1,NL
      IW(M,N)=0
      MW(M,N)=0
  503 ID(M,N)=0
      DO 504 N=1,KLC
  504 IC(N)=0
      READ 499,X
  499 FORMAT(F5.3)
      DO 510 IJ=1,NY
      DO 506 I=1,3
      READ 502,(A(I,J),J=1,NDATA)
  506 CONTINUE
      K=0
      DO 52 J=2,NDATA
      IF(A(1,J)-X) 1,1,2
    2 IF(A(2,J)-X) 3,3,4
    4 IF(A(3,J-1)-X) 5,5,6
    3 IF(A(3,J-1)-X) 7,7,8
    1 IF(A(2,J)-X) 9,9,10
   10 IF(A(3,J-1)-X) 11,11,12
    9 IF(A(3,J-1)-X) 60,60,13
    6 M=1
      Z=A(1,J)
      GO TO 50
    5 M=5
      Z=A(1,J)
      GO TO 50
    8 M=2
      Z=A(1,J)
      GO TO 50
    7 M=6
      Z=A(1,J)
      GO TO 50
   12 M=3
      Z=A(2,J)
      GO TO 50
   11 M=7
      Z=A(2,J)
      GO TO 50
   13 M=4
      Z=A(3,J-1)
```

```
      IF(A(3,J)-X) 14,14,15
   15 K=K+1
      RC(K)=A(3,J)
   14 GO TO 50
   60 M=8
      IF(A(3,J)-X) 16,16,17
   16 ID(M,1)=ID(M,1)+1
      GO TO 52
   17 IW(M,1)=IW(M,1)+1
      K=K+1
      RC(K)=A(3,J)
      GO TO 52
   50 CONTINUE
      DO 51 L=1,NL
      N=NL+1-L
      IF(Z-RLEV(N)) 51,51,18
   18 IF(A(3,J)-X) 19,19,20
   20 IW(M,N)=IW(M,N)+1
      IF(M-1) 71,72,71
   72 KK=IW(M,N)
      A1(N,KK)=A(1,J)
      B1(N,KK)=A(2,J)
      C1(N,KK)=A(3,J)
      GO TO 52
   71 IF(M-5) 73,74,73
   74 KK=IW(M,N)
      A5(N,KK)=A(1,J)
      B5(N,KK)=A(2,J)
      C5(N,KK)=A(3,J)
      GO TO 52
   73 IF(M-2) 75,76,75
   76 KK=IW(M,N)
      A2(N,KK)=A(1,J)
      C2(N,KK)=A(3,J)
      GO TO 52
   75 IF(M-6) 77,78,77
   78 KK=IW(M,N)
      A6(N,KK)=A(1,J)
      C6(N,KK)=A(3,J)
      GO TO 52
   77 IF(M-3) 79,80,79
   80 KK=IW(M,N)
      B3(N,KK)=A(2,J)
      C3(N,KK)=A(3,J)
      GO TO 52
   79 IF(M-7) 81,82,81
   82 KK=IW(M,N)
      B7(N,KK)=A(2,J)
      C7(N,KK)=A(3,J)
   81 GO TO 52
   19 ID(M,N)=ID(M,N)+1
      GO TO 52
   51 CONTINUE
   52 CONTINUE
```

```
      DO 40 J=1,K
      DO 41 L=1,KLC
      N=KLC+1-L
      IF(RC(J)-RLC(N)) 41,41,43
   43 IC(N)=IC(N)+1
      GO TO 40
   41 CONTINUE
   40 CONTINUE
      M=1
      DO 30 N=1,NL
      KK=IW(M,N)
      IF(KK) 30,30,31
   31 DO 32 K=1,KK
   32 PUNCH 100,M,N,A1(N,K),B1(N,K),C1(N,K)
  100 FORMAT(2I5,3F10.3)
   30 CONTINUE
      M=5
      DO 33 N=1,NL
      KK=IW(M,N)
      IF(KK) 33,33,34
   34 DO 35 K=1,KK
   35 PUNCH 100,M,N,A5(N,K),B5(N,K),C5(N,K)
   33 CONTINUE
      M=2
      DO 36 N=1,NL
      KK=IW(M,N)
      IF(KK) 36,36,37
   37 DO 38 K=1,KK
   38 PUNCH 100,M,N,A2(N,K),C2(N,K)
   36 CONTINUE
      M=6
      DO 90 N=1,NL
      KK=IW(M,N)
      IF(KK) 90,90,91
   91 DO 92 K=1,KK
   92 PUNCH 100,M,N,A6(N,K),C6(N,K)
   90 CONTINUE
      M=3
      DO 93 N=1,NL
      KK=IW(M,N)
      IF(KK) 93,93,94
   94 DO 95 K=1,KK
   95 PUNCH 100,M,N,B3(N,K),C3(N,K)
   93 CONTINUE
      M=7
      DO 26 N=1,NL
      KK=IW(M,N)
         IF(KK)26,26,28
  28     DO 27 K=1,KK
   27 PUNCH 100,M,N,B7(N,K),C7(N,K)
   26 CONTINUE
      DO 21 M=1,7
      DO 21 N=1,NL
   21 MW(M,N)=MW(M,N)+IW(M,N)
      DO 22 M=1,7
```

```
      DO 22 N=1,NL
   22 IW(M,N)=0
  510 CONTINUE
      DO 23 M=1,7
      DO 23 N=1,NL
   23 PUNCH 101,M,N,MW(M,N),ID(M,N)
  101 FORMAT(4(10X,I5))
      M=8
      N=1
      PUNCH 101,M,N,IW(M,N),ID(M,N)
      DO 24 N=1,KLC
   24 PUNCH 102,N,IC(N)
  102 FORMAT(2(10X,I5))
      STOP
      END
```

```
C     OBSERVED CUMULATIVE DISTRIBUTIONS FOR ALL STATIONS
      DIMENSION ICL(3,25),A(3,100),RL(25)
      READ 1,NDATA,NL,NY
    1 FORMAT(5I5)
      READ 2,(RL(N),N=1,NL)
    2 FORMAT(16F5.2)
      DO 100 N=1,NL
      DO 100 I=1,3
  100 ICL(I,N)=0
      DO 200 K=1,NY
      DO 101 I=1,3
      READ 102,(A(I,J),J=1,NDATA)
  102 FORMAT(16F5.3)
  101 CONTINUE
      DO 202 I=1,3
      DO 201 J=1,NDATA
      DO 203 L=1,NL
      N=NL+1-L
      IF(A(I,J)-RL(N)) 203,204,204
  204 ICL(I,N)=ICL(I,N)+1
      GO TO 201
  203 CONTINUE
  201 CONTINUE
  202 CONTINUE
  200 CONTINUE
      DO 206 I=1,3
      DO 207 N=2,NL
      ICL(I,N)=ICL(I,N)+ICL(I,N-1)
  207 CONTINUE
      DO 208 N=1,NL
      PUNCH 210,N,ICL(I,N)
  210 FORMAT(10X,I5,10X,I5)
  208 CONTINUE
  206 CONTINUE
      STOP
      END
```

```
C      BIVARIATE CORRELATION ANALYSIS FOR ORDINARY AND TRANSFORMED DATA
       DIMENSION ND(10),X(100),Y(100),RNX(60),RNY(60),R1X(50),R1Y(50)
       DIMENSION R2X(50),R2Y(50)
       READ 1,NL1,NL2,NLN
       READ 20,(RNX(I),I=1,NLN)
       READ 20,(RNY(I),I=1,NLN)
       READ 20,(R1X(I),I=1,NL1)
       READ 20,(R1Y(I),I=1,NL1)
       READ 20,(R2X(I),I=1,NL2)
       READ 20,(R2Y(I),I=1,NL2)
  20   FORMAT(16F5.3)
       READ 1,NS
   1   FORMAT(16I5)
       READ 1,(ND(I),I=1,NS)
       DO 100 I=1,NS
       NN=0
       K=ND(I)
       DO 101 J=1,K
       READ 2,M,NT,X(J),Y(J)
   2   FORMAT(2I5,2F10.3)
 101   CONTINUE
 102   CONTINUE
       S1=0.
       S2=0.
       S3=0.
       S4=0.
       S5=0.
       DO 103 J=1,K
       S1=S1+X(J)
       S2=S2+X(J)*X(J)
       S3=S3+Y(J)
       S4=S4+Y(J)*Y(J)
       S5=S5+X(J)*Y(J)
 103   CONTINUE
       AN=K
       B=(S5-S1*S3/AN)/(S2-S1*S1/AN)
       A=S3/AN-B*S1/AN
       R=B*B*(S2-S1*S1/AN)/(S4-S3*S3/AN)
       VAR=(1.-R)*(S4-S3*S3/AN)/(AN-2.)
       IF(R) 50,50,51
  51   R=SQRTF(R)
  50   CONTINUE
       PUNCH 1,M,NT
       PUNCH 3,A,B,R,VAR
   3   FORMAT(4E16.7//)
       IF(NN-1) 104,100,100
 104   CONTINUE
       DO 300 J=1,K
       DO 10 L=1,NL1
       N=NL1+1-L
       IF(X(J)-R1X(N)) 10,10,11
  11   BS=(X(J)-R1X(N))*(R1Y(N+1)-R1Y(N))/(R1X(N+1)-R1X(N))+R1Y(N)
       GO TO 12
  10   CONTINUE
```

```
   12 DO 13 L=1,NLN
      N=NLN+1-L
      IF(BS-RNY(N)) 13,13,14
   14 X(J)=(BS-RNY(N))*(RNX(N+1)-RNX(N))/(RNY(N+1)-RNY(N))+RNX(N)
      GO TO 30
   13 CONTINUE
   30 DO 15 L=1,NL2
      N=NL2+1-L
      IF(Y(J)-R2X(N)) 15,15,16
   16 BS=(Y(J)-R2X(N))*(R2Y(N+1)-R2Y(N))/(R2X(N+1)-R2X(N))+R2Y(N)
      GO TO 17
   15 CONTINUE
   17 DO 18 L=1,NLN
      N=NLN+1-L
      IF(BS-RNY(N)) 18,18,19
   19 Y(J)=(BS-RNY(N))*(RNX(N+1)-RNX(N))/(RNY(N+1)-RNY(N))+RNX(N)
      GO TO 31
   18 CONTINUE
   31 CONTINUE
      PUNCH 2,M,NT,X(J),Y(J)
  300 CONTINUE
      NN=NN+1
      GO TO 102
  100 CONTINUE
      STOP
      END
```

```
C     TRANSFORMATION TO @NORMAL@ FOR MULTIVARIATE CASES
      DIMENSION NL(3),RNX(60),RNY(60),RX(3,50),RY(3,50),ND(10),X(3,100)
      READ 1,(NL(I),I=1,3),NLN
      READ 2,(RNX(I),I=1,NLN)
      READ 2,(RNY(I),I=1,NLN)
      DO 10 I=1,3
      NX=NL(I)
      READ 2,(RX(I,J),J=1,NX)
      READ 2,(RY(I,J),J=1,NX)
   10 CONTINUE
    2 FORMAT(16F5.3)
      READ 1,NS
      READ 1,(ND(I),I=1,NS)
    1 FORMAT(16I5)
      DO 100 II=1,NS
      K=ND(II)
      DO 11 J=1,K
      READ 3,MM,NN,(X(I,J),I=1,3)
      PUNCH 4,(X(I,J),I=1,3)
   11 CONTINUE
    3 FORMAT(2I5,3F10.3)
    4 FORMAT(3F10.3)
      PUNCH 1,MM,NN
      DO 300 J=1,K
      DO 200 I=1,3
      M=NL(I)
      DO 12 L=1,M
      N=M+1-L
      IF(X(I,J)-RX(I,N)) 12,12,13
   13 BS=(X(I,J)-RX(I,N))*(RY(I,N+1)-RY(I,N))/(RX(I,N+1)-RX(I,N))+RY(I,N
     1)
      GO TO 14
   12 CONTINUE
   14 DO 15 L=1,NLN
      N=NLN+1-L
      IF(BS-RNY(N)) 15,15,16
   16 X(I,J)=(BS-RNY(N))*(RNX(N+1)-RNX(N))/(RNY(N+1)-RNY(N))+RNX(N)
      GO TO 200
   15 CONTINUE
  200 CONTINUE
      PUNCH 5,(X(I,J),I=1,3)
    5 FORMAT(3F10.5)
  300 CONTINUE
  100 CONTINUE
      STOP
      END
```

```
C     DAILY RAINFALL RUNOFF MODEL BY J.T.B.OBEYSEKERA
      DIMENSION A(10),QOB(150),PER(5),R(25),T(40,7),QC(40,30),QCA(40)
      DIMENSION QD(450),W(8,8),RAIN(150,8),RF(8),API(150),WEEK(150),
     1RAN(150),AINCR(4,10)
      DIMENSION YY(150),XX(150)
      READ(5,1) INDEX
       READ(5,1) NTRY,NA,ND
       WRITE(6,1) NTRY,NA,ND
       READ (5,1) NORD,NRG,NDAY
       WRITE(6,1) NORD,NRG,NDAY
       READ (5,71) AA,BB,CC,DD,EE
       WRITE(6,71) AA,BB,CC,DD,EE
71     FORMAT(8F10.7)
1      FORMAT(16I5)
       READ (5,3) (A(I),I=1,NA)
       WRITE(6,3) (A(I),I=1,NA)
       READ (5,300) NDALES,WEEKST,API(1),FACT,APIK
       WRITE(6,300) NDALES,WEEKST,API(1),FACT,APIK
300    FORMAT(I5,5F10.5)
       READ (5,71) ACC
       WRITE(6,71) ACC
C
       READ(5,1) NIN
       READ(5,3) EMAX
       DO 399 I=1,NA
399    READ(5,3) (AINCR(I,J),J=1,NIN)
       DO 20 I=1,NA
       READ (5,71) (W(I,J),J=1,NRG)
       WRITE(6,71) (W(I,J),J=1,NRG)
20     CONTINUE
C
       NDM=24/ND
       DO 21 I=1,NDAY
       READ (5,3) (RAIN(I,L),L=1,NRG)
       WRITE(6,3) (RAIN(I,L),L=1,NRG)
3      FORMAT(8F10.3)
21     CONTINUE
       READ (5,3) (QOB(I),I=1,NORD)
       WRITE(6,3) (QOB(I),I=1,NORD)
       DO 199 II=1,NDALES
       WEEK(II)=WEEKST
199    CONTINUE
30     II=II+1
       WEEKST=WEEKST+1
       JJ=II+6
       DO 310 K=II,JJ
       IF(K.GT.NDAY) GO TO 320
       WEEK(K)=WEEKST
310    CONTINUE
       II=K
       GO TO 30
320    CONTINUE
       TOT=0.0
       DO 321 I=1,NA
       TOT=TOT+A(I)
321    CONTINUE
```

```
      S1=0.0
      S2=0.0
      DO 74 M=1,NORD
      S1=S1+QOB(M)
74    S2=S2+QOB(M)*QOB(M)
      AN=NORD
      VAROB=S2-S1*S1/AN
      VOL=0.0
      DO 200 II=1,NDAY
      DO 40 MM=1,NA
      RF(MM)=0.0
      DO 40 L=1,NRG
40    RF(MM)=RF(MM)+W(MM,L)*RAIN(II,L)
      RAN(II)=0.0
      DO 31 MM=1,NA
      RAN(II)=RAN(II)+RF(MM)*A(MM)
31    CONTINUE
      RAN(II)=RAN(II)/TOT
      API(II+1)=API(II)*APIK+RAN(II)
      ROC=AA+BB*RAN(II)+CC*API(II)+DD*1.0+EE*WEEK(II)
      ROC=ROC*FACT
      VOL=VOL+ROC*RAN(II)*TOT
200   CONTINUE
     IF(INDEX.EQ.1) GO TO 871
      FACT=S1/VOL
      WRITE(6,325) FACT
325   FORMAT(/,10X,@NEW VALUE OF FACTOR =@,F10.5//)
871   CONTINUE
      WRITE(6,326)
326   FORMAT(//,10X,@RAINFALL@,30X,@API@,30X,@WEEK NUMBER@//)
      WRITE(6,327) (RAN(II),API(II),WEEK(II),II=1,NDAY)
327   FORMAT(10X,F8.3,27X,F8.3,30X,F8.3)
      DO 101 IJ=1,NTRY
      READ (5,3) (PER(I),I=1,NDN)
     READ(5,3) (R(J),J=1,NA)
     NAN=NA
     IF(INDEX.EQ.1) NAN=1
     DO 100 KN=1,NAN
      JK=NA+1-KN
      RINT=R(JK)
      RMAX=R(JK)
     IF(INDEX.EQ.1) NIN=1
      DO 111 KM=1,NIN
      R(JK)=RINT+AINCR(JK,KM)
      WRITE(6,322) IJ,JK,KM
 322  FORMAT(1H2,10X,@TRIAL NUMBER =@,I3//,10X,@THE R IS VARIED FOR ARE
     1A NO. =@,I3//,10X,@INCREMENT NO. =@,I3///)
      WRITE(6,323) (PER(I),I=1,NDN)
323   FORMAT(10X,@PERCENTAGES@/,10X,5F10.3)
      WRITE(6,324) (R(J),J=1,NA)
324   FORMAT(/,10X,@VALUES OF R@/,10X,5F10.3)
C     COMPUTE TRAVEL COEFFICIENTS
      T(1,1)=R(1)
      DO 50 I=2,NA
```

```
50      T(1,I)=0.0
        J=1
        S=0.0
4       J=J+1
        DO 51 L=1,NA
        IF(L-1) 6,6,7
6       T(J,L)=T(J-1,L)*(1.-R(L))
        GO TO 51
7       T(J,L)=(1.-R(L))*T(J-1,L)+R(L)*T(J-1,L-1)
51      CONTINUE
        S=S+T(J,NA)
        IF(S.LT.ACC) GO TO 4
        N2=J+NDN-1
        M1=NA*NDN
C       COMPUTE DAILY RUNOFF VALUES
        DO 401 II=1,NDAY
        ROC=AA+BB*RAN(II)+CC*API(II)+DD*1.0+EE*WEEK(II)
        ROC=ROC*FACT
        DO 60 M=1,N2
        DO 60 N=1,M1
60      QC(M,N)=0.0
        DO 54 MM=1,NA
        RF(MM)=0.0
        DO 440 L=1,NRG
440     RF(MM)=RF(MM)+W(MM,L)*RAIN(II,L)
        N3=NDN*(MM-1)+1
        N4=N3+NDN-1
        DO 55 N=N3,N4
        N5=MM+N-N3
        N6=N5+J-MM
        LN=N-N3+1
        DO 56 M=N5,N6
        LM=M-N5+MM
        QC(M,N)=A(MM)*PER(LN)*RF(MM)*ROC*T(LM,MM)/100.
56      CONTINUE
55      CONTINUE
54      CONTINUE
        DO 57 M=1,N2
        QCA(M)=0.0
        DO 57 N=1,M1
57      QCA(M)=QCA(M)+QC(M,N)
        IF(II-1) 58,58,59
58      DO 61 K=1,N2
61      QD(K)=QCA(K)
        GO TO 401
59      N7=N2-NDN
        DO 62 M=1,N7
        K=NDN*(II-1)+M
        AX=QD(K)
        BX=QCA(M)
62      QD(K)=AX+BX
        N7=N7+1
        DO 64 M=N7,N2
        K=K+1
```

```
64     QD(K)=QCA(M)
       DO 63 M=1,NDN
       KK=K+M
63     QD(KK)=0.0
401    CONTINUE
       KK=KK-NDN
       NX=KK/NDN
       N=(NX+1)*NDN-KK
       DO 41 L=1,N
       KK=KK+L
41     QD(KK)=0.0
       NX=NX+1
       DO 42 M=1,NX
       S=0.0
       N1=(M-1)*NDN+1
       N2=N1+NDN-1
       DO 43 K=N1,N2
43     S=S+QD(K)
42     QD(M)=S
       SUM=0.0
       S=0.0
       IF(NORD-NX) 80,80,81
80     N10=NORD
       GO TO 82
81     N10=NX
82     DO 73 M=1,N10
       SUM=SUM+QD(M)
73     S=S+(QOB(M)-QD(M))**2
       EFF=(1.-S/VAROB)*100.
       WRITE(6,403) (QD(L),L=1,NX)
403    FORMAT(//,55X,@COMPUTED DAILY RUNOFF@//,(12F11.3))
       WRITE(6,404) (QOB(L),L=1,NORD)
404    FORMAT(//,55X,@OBSERVED DAILY RUNOFF@//,(12F11.3))
       WRITE(6,72) SUM,S1,S,VAROB,EFF
72     FORMAT(///,20X,@COMPUTED VOLUME =@,F15.3/,20X,@OBSERVED VOLUME =@
      1,F15.3//,20X,@SUM OF OBS-CALC SQUARED =@,F15.3//,20X,@OBSERVED VAR
      2IANCE =@,F15.3//,20X,@EFFICIENCY =@,F10.3)
       IF(EFF.LT.EMAX) GO TO 351
       EMAX=EFF
       RMAX=R(JK)
      DO 708 IK=1,NX
708   YY(IK)=QD(IK)
      NXX=NX
351    CONTINUE
       WRITE(6,352) EMAX
352    FORMAT(10X,@MAXIMUM EFFICIENCY SO FAR ACHIEVED =@,F10.3///)
111    CONTINUE
       R(JK)=RMAX
       WRITE(6,353) EMAX,(R(L),L=1,NA)
353    FORMAT(///5X,@MAXIMUM EFFICIENCY OF@,F10.3,@FOR THE SET OF R VALU
      1ES@,5F10.4//)
100    CONTINUE
101    CONTINUE
      WRITE(6,707)
707   FORMAT(1H2)
```

```
      XMIN=0.0
      XMAX=110.0
      XL=12.0
      XD=5.0
      YMIN=0.0
      YMAX=3000.0
      YL=11.0
      YD=500.0
      PAUSE@POSITION PEN ON PLOTTER@
      CALL PLOT(101,XMIN,XMAX,XL,XD,YMIN,YMAX,YL,YD)
      DO 709 IK=1,95
709   XX(IK)=IK
      DO 711 I=1,NORD
      CALL PLOT(10,XX(I),QOB(I))
711   CONTINUE
      CALL PLOT(99)
      CALL PLOT(91,XMIN,YMIN)
      DO 712 I=1,NXX
      CALL PLOT(12,XX(I),YY(I))
 712  CONTINUE
      STOP
      END
```

```
C       STOCHASTIC DAILY STREAMFLOW MODEL  BY J.T.B.OBEYSEKERA
        INTEGER OUT
         COMMON/AA/GX(3,50),GY(3,50),RNX(100),RNY(100),NG(3),NLN
         COMMON/BB/A(3,100),NS,NDAY
         COMMON/CC/HWD(3,2,2,2,4),A10(3,2,2,2,4),B10(3,2,2,2,4),
       1 B11(3,2,2,2,4),VARD(3,2,2,2,4),R2G(3,2,2,2,4),NBSTA(3),NESTA(3),
       2 RLEV(4),RX(3,50),RY(3,50),NR(3),ZAZ
         COMMON/DD/ SURA(3),S2RA(3),S3RA(3),SUMRA(3),SQMRA(3),CUBRA(3)
        COMMON/EE/X,NQ(10)
         COMMON/FF/NYY(10)
        COMMON/GG/NA,ND,NDN,NRG,AA,BB,CC,DD,EE,AR(10),W(8,8),ACC,PER(5),R(
       15),NDALES,WEEKST,FACT,APIK
        COMMON/HH/DIR(25),BAS(25),NBL
        COMMON/ZZ/JAY,AP1
        DIMENSION NSER(10)
C
         IN=5
         OUT=6
         READ (5,1) JAY
         WRITE(6,1) JAY
        READ(5,3) AP1
         READ(5,1) NA,ND,NRG
         WRITE(6,1) NA,ND,NRG
         READ(5,71) AA,BB,CC,DD,EE
   71    FORMAT(8F10.7)
         READ(5,3) (AR(I),I=1,NA)
        WRITE(6,3)(AR(I),I=1,NA)
         READ(5,997) NDALES,WEEKST,FACT,APIK
997      FORMAT(I5,5F10.5)
         READ(5,71) ACC
        DO 239 I=1,NA
         READ(5,71) (W(I,J),J=1,NRG)
239      CONTINUE
         NDN=24/ND
         READ(5,3) (PER(I),I=1,NDN)
         READ(5,3) (R(J),J=1,NA)
         READ(5,1)NBL
         WRITE(6,1) NBL
         READ(5,3) (DIR(L),L=1,NBL)
         WRITE(6,3) (DIR(L),L=1,NBL)
         READ(5,3) (BAS(L),L=1,NBL)
         WRITE(6,3) (BAS(L),L=1,NBL)
         READ(IN,1) NDAY,NS
         WRITE(OUT,1) NDAY,NS
    1    FORMAT(16I5)
         READ(IN,1) NLN,(NG(I),I=1,NS),(NR(I),I=1,NS)
         WRITE(OUT,1) NLN,(NG(I),I=1,NS),(NR(I),I=1,NS)
        DO 10 I=1,NS
         NX=NG(I)
         NY=NR(I)
         READ (IN,2) (GX(I,J),J=1,NX)
         WRITE(OUT,8) (GX(I,J),J=1,NX)
         READ (IN ,2) (GY(I,J),J=1,NX)
         WRITE(OUT,8) (GY(I,J),J=1,NX)
```

```
      READ (IN ,2) (RX(I,J),J=1,NY)
      WRITE(OUT,8) (RX(I,J),J=1,NY)
      READ(IN ,2) (RY(I,J),J=1,NY)
      WRITE(OUT,8) (RY(I,J),J=1,NY)
10    CONTINUE
8     FORMAT(/,15F8.3)
2     FORMAT(16F5.3)
      READ (IN ,2) (RNX(I),I=1,NLN)
      WRITE(OUT,8) (RNX(I),I=1,NLN)
      READ (IN ,2) (RNY(I),I=1,NLN)
      WRITE(OUT,8) (RNY(I),I=1,NLN)
     DO 100 K4=1,2
      DO 100 K5=1,2
       DO 100 K2=1,2
       L=3
       IF(K2.EQ.1.AND.K5.EQ.1.AND.K4.EQ.1) L=1
        DO 100 MM=1,L
        READ (IN ,3) (HWD(I,K2,K4,K5,MM),I=1,NS)
        WRITE(OUT,3) (HWD(I,K2,K4,K5,MM),I=1,NS)
100     CONTINUE
3     FORMAT(8F10.5)
C
     DO 200 K4=1,2
      DO 200 K2=1,2
       DO 200 MM=1,3
      READ(IN,4)    A10(2,K2,K4,2,MM),B11(2,K2,K4,2,MM),
     1 R2G(2,K2,K4,2,JM),VARD(2,K2,K4,2,MM)
      WRITE(OUT,4) A10(2,K2,K4,2,MM),B11(2,K2,K4,2,MM),
     2 R2G(2,K2,K4,2,MM),VARD(2,K2,K4,2,MM)
200   CONTINUE
4     FORMAT(8F10.5)
C
     DO 300 K4=1,2
      DO 300 MM=1,3
      READ (IN ,4) A10(3,2,K4,2,MM),B10(3,2,K4,2,MM),
     1 B11(3,2,K4,2,MM),R2G(3,2,K4,2,MM),VARD(3,2,K4,2,MM)
      WRITE(OUT,4) A10(3,2,K4,2,MM),B10(3,2,K4,2,MM),
     1 B11(3,2,K4,2,MM),R2G(3,2,K4,2,MM),VARD(3,2,K4,2,MM)
300   CONTINUE
C
     DO 350 K4=1,2
      DO 350 MM=1,3
      READ (IN ,4) A10(3,1,K4,2,MM),B11(3,1,K4,2,MM),
     1 R2G(3,1,K4,2,MM),VARD(3,1,K4,2,MM)
      WRITE(OUT,4) A10(3,1,K4,2,MM),B11(3,1,K4,2,MM),
     1 R2G(3,1,K4,2,MM),VARD(3,1,K4,2,MM)
350   CONTINUE
C
     DO 375 K4=1,2
      DO 375 MM=1,3
```

```
      READ (IN ,4) A10(3,2,K4,1,MM),B10(3,2,K4,1,MM),
     1 R2G(3,2,K4,1,MM),VARD(3,2,K4,1,MM)
      WRITE(OUT,4) A10(3,2,K4,1,MM),B10(3,2,K4,1,MM),
     1 R2C(3,2,K4,1,MM),VARD(3,2,K4,1,MM)
375   CONTINUE
C
      READ (IN ,3) (RLEV(I),I=1,3)
      WRITE(OUT,3) (RLEV(I),I=1,3)
      READ (IN ,1) (NBSTA(I),I=1,3)
      WRITE(OUT,1) (NBSTA(I),I=1,3)
      READ (IN ,1) (NESTA(I),I=1,3)
      WRITE(OUT,1) (NESTA(I),I=1,3)
      READ (IN ,3) ZAZ,X
      WRITE(OUT,3) ZAZ,X
C
      READ (IN,1) INDEX,ISER
      WRITE(OUT,1) INDEX,ISER
      READ (IN ,1) (NSER(I),I=1,ISER)
      WRITE(OUT,1) (NSER(I),I=1,ISER)
      READ(IN,1) (NYY(I),I=1,ISER)
      WRITE(OUT,1) (NYY(I),I=1,ISER)
      READ (IN ,3) (A(I,1),I=1,NS)
      WRITE(OUT,3) (A(I,1),I=1,NS)
C
      DO 1000 IL=1,ISER
      READ(IN,999) NQ(IL)
999   FORMAT(I9)
      IX=NQ(IL)
       NL=NSER(IL)
       NYES=NYY(IL)
      CALL GENERA(NL,INDEX,NYES,IX)
1000  CONTINUE
      STOP
      END



      SUBROUTINE GENERA(NYEAR,INDEX,NYES,IX)
C     SUBROUTINE FOR STOCHASTIC DAILY RAINFALL GENERATION
      INTEGER OUT
       COMMON/AA/GX(3,50),GY(3,50),RNX(100),RNY(100),NG(3),NLN
       COMMON/BB/A(3,100),NS,NDAY
       COMMON/CC/HWD(3,2,2,2,4),A1C(3,2,2,2,4),B10(3,2,2,2,4),
     2 B11(3,2,2,2,4),VARD(3,2,2,2,4),R2G(3,2,2,2,4),NBSTA(3),NESTA(3),
     3 RLEV(4),RX(3,50),RY(3,50),NR(3),ZAZ
       COMMON/DD/SURA(3),S2RA(3),S3RA(3),SUMRA(3),SQMRA(3),CUBRA(3)
      COMMON/EE/X,NQ(10)
       COMMON/FF/NYY(10)
      COMMON/GG/ NA,ND,NDN,NRG,AA,BB,CC,DD,EE,AR(10),W(8,8),ACC,PER(5),R
```

```
      1(5),NDALES,WEEKST,FACT,APIK
       COMMON/HH/DIR(25),BAS(25),NBL
       COMMON/ZZ/JAY,AP1
       DO 800 I=1,NS
        SUMRA(I)=0.0
        SQMRA(I)=0.0
        CUBRA(I)=0.0
800     CONTINUE
        NEX=0
        NL=3
       DO 700 IJ=1,NYEAR
        NIN=0
        NOB=0
        OUT=6
        NRN=0
       DO 600 I=1,NS
        SURA(I)=A(I,1)
        S2RA(I)=A(I,1)*A(I,1)
        S3RA(I)=A(I,1)*A(I,1)*A(I,1)
600    CONTINUE
C
       DO 500 K=2,NDAY
        DO 475 N=1,NS
         ISB=NBSTA(N)
         ISE=NESTA(N)
         IC=1
         ID=1
         IF(N.NE.1) ID=0
         IF(N.GT.2) IC=0
C
         A2=A(ISB,K-IC)
         A4=A(N,K-1)
         A5=A(ISE,K-ID)
         K2=1
         IF(A2.GT.X) K2=2
         K4=1
         IF(A4.GT.X) K4=2
         K5=1
         IF(A5.GT.X) K5=2
         IF(N.EQ.1.AND.K2.EQ.1.AND.K4.EQ.1.AND.K5.EQ.1) GO TO 100
         IF(N.GT.2) GO TO 35
         IF(N.EQ.2) GO TO 40
         Z=A4
         IF(K4.EQ.2) GO TO 50
         Z=A5
         IF(K5.EQ.2) GO TO 50
         Z=A2
         IF(K2.EQ.2) GO TO 50
         GO TO 100
35       Z=A5
         IF(K5.EQ.2) GO TO 50
         Z=A2
         IF(K2.EQ.2) GO TO 50
```

```
      Z=A4
      IF(K4.EQ.2) GO TO 50
      GO TO 100
40    Z=A5
      IF(K5.EQ.2) GO TO 50
      Z=A4
      IF(K4.EQ.2) GO TO 50
      Z=A2
      IF(K2.EQ.2) GO TO 50
      GO TO 100
50    CONTINUE
     DO 51 IS=1,NL
      MM=NL+1-IS
      RA=RLEV(MM)
      IF(Z.GT.RA) GO TO 52
51    CONTINUE
52   CALL RANDUM(IX,IY,YF)
      IX=IY
      IF(YF.GT.HWD(N,K2,K4,K5,MM)) GO TO 53
      IF(N.EQ.1) GO TO 110
      IF(N.GT.2.AND.K2.EQ.2.AND.K5.EQ.2) GO TO 60
      IF(N.GT.2.AND.K2.EQ.2.AND.K5.EQ.1) GO TO 70
      IF(N.GE.2.AND.K5.EQ.2) GO TO 80
      GO TO 110
60   CALL TRANSF(A2,ISB)
     CALL TRANSF(A5,ISE)
      Z=A10(N,2,K4,2,MM)+B10(N,2,K4,2,MM)*A2+B11(N,2,K4,2,MM)*A5
      IF(R2G(N,2,K4,2,MM).LE.ZAZ) GO TO 195
      Z2=VARD(N,2,K4,2,MM)
      NIN=NIN.1
     CALL GAUSSB(IX,Z2,Z,ZX)
     CALL SFNART(ZX,N)
      A(N,K)=ZX
      NRN=NRN+1
      GO TO 476
70   CALL TRANSF(A2,ISB)
      Z=A10(N,2,K4,1,MM)+B10(N,2,K4,1,MM)*A2
      IF(R2G(N,2,K4,1,MM).LE.ZAZ) GO TO 195
      Z2=VARD(N,2,K4,1,MM)
      NIN=NIN.1
     CALL GAUSSB(IX,Z2,Z,ZX)
     CALL SFNART(ZX,N)
      A(N,K)=ZX
      NRN=NRN+1
      GO TO 476
80   CALL TRANSF(A5,ISE)
      Z=A10(N,K2,K4,2,MM)+B11(N,K2,K4,2,MM)*A5
      IF(R2G(N,K2,K4,2,MM).LE.ZAZ) GO TO 195
      Z2=VARD(N,K2,K4,2,MM)
      NIN=NIN.1
     CALL GAUSSB(IX,Z2,Z,ZX)
     CALL SFNART(ZX,N)
      A(N,K)=ZX
      NRN=NRN+1
      GO TO 476
100  CALL RANDUM(IX,IY,YF)
```

```
      MN=1
      IX=IY
      IF(YF.GT.HWD(N,K2,K4,K5,1)) GO TO 53
110   CALL RANDUM(IX,IY,YF)
      IX=IY
      NX=NR(N)
      DO 120 KA=2,NX
      IZ=KA
      IF(YF.GE.RY(N,IZ-1).AND.YF.LT.RY(N,IZ)) GO TO 130
120   CONTINUE
130   BT=(YF-RY(N,IZ-1))*(RX(N,IZ)-RX(N,IZ-1))/
     1 (RY(N,IZ)-RY(N,IZ-1))+RX(N,IZ-1)
      A(N,K)=BT
      NRN=NRN+1
      GO TO 476
53    A(N,K)=0.0
      NOB=NOB.1
      GO TO 476
195   CALL RANDUM(IX,IY,YF)
      IX=IY
      NX=NG(N)
      DO 220 KA=2,NX
      IZ=KA
      IF(YF.GE.GY(N,IZ-1).AND.YF.LT.GY(N,IZ)) GO TO 230
220   CONTINUE
230   BT=(YF-GY(N,IZ-1))*(GX(N,IZ)-GX(N,IZ-1))/
     1 (GY(N,IZ)-GY(N,IZ-1))+GX(N,IZ-1)
      A(N,K)=BT
      NRN=NRN+1
476   CONTINUE
      A3=A(N,K)
      SURA(N)=SURA(N)+A3
      S2RA(N)=S2RA(N)+A3*A3
      S3RA(N)=S3RA(N)+A3*A3*A3
475   CONTINUE
500   CONTINUE
      WRITE(OUT,111)
111   FORMAT(5X,4HYEAR,10X,11HSEASON MEAN ,10X,7HSTD.DEV ,10X,
     1 8HSKEWNESS ,10X,12HSTATION NO.    )
      DO 400 N=1,NS
      A5=NDAY
      A3=SURA(N)/(A5)
      B3=S2RA(N)/(A5)-(SURA(N)*SURA(N))/(A5*A5)
      B3=SQRT(B3)
      G=((A5*A5)*S3RA(N)-3*A5*SURA(N)*S2RA(N)+2*SURA(N)*SURA(N)
     1 *SURA(N))/(A5*(A5-1)*(A5-2)*B3*B3*B3)
      WRITE(OUT,222) IJ,A3,B3,G,N
222   FORMAT(/,5X,I3,11X,F9.3,12X,F6.3,11X,F7.3,14X,I2)
400   CONTINUE
      WRITE(OUT,202) NIN
202   FORMAT(10X,@NO. OF TIMES GAUSS CALLED =@,I4)
      WRITE(OUT,1) NOB
1     FORMAT(20X,@ NUMBER OF DRY DAYS IN THE SEASON = @,I7)
      WRITE(OUT,223) NRN
223   FORMAT(20X,36HNUMBER OF RAINY DAYS IN THE SEASON =, I7)
      IF(INDEX.NE.1) GO TO 402
      NEX=NEX+1
      IF(NEX.GT.NYES) GO TO 402
```

```
      CALL WRTOUT
402    CONTINUE
      DO 403 N=1,NS
       SUMRA(N)=SUMRA(N)+SURA(N)
       SQMRA(N)=SQMRA(N)+SURA(N)*SURA(N)
       CUBRA(N)=CUBRA(N)+SURA(N)*SURA(N)*SURA(N)
403    CONTINUE
      TEMP=WEEKST
      CALL SIMULA
      WEEKST=TEMP
700   CONTINUE
       WRITE(OUT,333)
333   FORMAT(1H2)
      DO 4000 N=1,NS
       WRITE(OUT,2222)
       A5=NYEAR
       A3=SUMRA(N)/A5
      B3=SQMRA(N)/(A5-1)-(SUMRA(N)*SUMRA(N))/(A5*(A5-1))
       B3=SQRT(B3)
       G=((A5*A5)*CUBRA(N)-3*A5*SUMRA(N)*SQMRA(N)+2*SUMRA(N)*SUMRA(N)
     1 *SUMRA(N))/(A5*(A5-1)*(A5-2)*B3*B3*B3)
       WRITE(OUT,334) A3,B3,G,N
4000   CONTINUE
2222   FORMAT(//,24X,94HYEARLY MEAN RAIN        STA.DEV. OF YEARLY RAIN
     1  SKEW OF YEARLY RAIN            STATION NUMBER     )
334    FORMAT(/,29X,F8.2,16X,F9.2,19X,F7.3,25X,I2)
      RETURN
      END

      SUBROUTINE WRTOUT
      INTEGER OUT
       COMMON/BB/A(3,100),NS,NDAY
       OUT=6
      DO 100 I=1,NS
       WRITE(OUT,102) I
       WRITE(OUT,101)(A(I,K),K=1,NDAY)
100   CONTINUE
102    FORMAT(20X,6HSEASON,10X,31HDAILY  RAINFALL - STATION  NO.=,I3)
101    FORMAT(15F8.3)
      RETURN
      END

      SUBROUTINE TRANSF(AS,I)
      INTEGER OUT
       COMMON/AA/GX(3,50),GY(3,50),RNX(100),RNY(100),NG(3),NLN
       OUT=6
       M=NG(I)
      DO 12 L=1,M
       N=M+1-L
       IF(AS.GT.GX(I,N)) GO TO 13
12    CONTINUE
13     CONTINUE
      IF(L.NE.1) GO TO 14
      AS=GX(I,N)
```

```
      GY(I,N+1)=GY(I,N)
      GX(I,N+1)=GX(I,N)+1.0
      WRITE(OUT,1) N
1     FORMAT(I3,24HLIMIT EXCEEDED IN TRANSF   )
14    CONTINUE
      BS=(AS-GX(I,N))*(GY(I,N+1)-GY(I,N))/
     1 (GX(I,N+1)-GX(I,N))+GY(I,N)
      DO 15 L=1,NLN
      N=NLN+1-L
      IF(BS.GT.RNY(N)) GO TO 16
15    CONTINUE
16    AS=(BS-RNY(N))*(RNX(N+1)-RNX(N))/
     1 (RNY(N+1)-RNY(N))+RNX(N)
      RETURN
      END

      SUBROUTINE SFNART(AS,I)
      INTEGER OUT
      COMMON/AA/GX(3,50),GY(3,50),RNX(100),RNY(100),NG(3),NLN
      OUT=6
      M=NG(I)
      DO 15 L=1,NLN
      N=NLN+1-L
      IF(AS.GT.RNX(N)) GO TO 17
15    CONTINUE
      WRITE(OUT,1) N
1     FORMAT(I3,24HLIMIT EXCEEDED IN SFNART   )
      AS=RNX(N)
17    IF(L.NE.1) GO TO 16
      AS=RNX(N)
      RNY(N+1)=RNY(N)
      RNX(N+1)=RNX(N)+1.0
16    BS=(AS-RNX(N))*(RNY(N+1)-RNY(N))/(RNX(N+1)-RNX(N))+RNY(N)
      DO 12 L=1,M
      N=M+1-L
      IF(BS.GT.GY(I,N)) GO TO 13
12    CONTINUE
13    AS=(BS-GY(I,N))*(GX(I,N+1)-GX(I,N))/(GY(I,N+1)-GY(I,N))+GX(I,N)
      RETURN
      END
```

```
      SUBROUTINE SIMULA
C     SUBROUTINE TO TRANSFORM DAILY RAINFALL TO DAILY RUNOFF
      DIMENSION RAN(150),API(150),WEEK(150),QD(450),RF(8),T(40,7),QC(40,
     130),QCA(40)
      COMMON/GG/ NA,ND,NDN,NRG,AA,BB,CC,DD,EE,AR(10),W(8,8),ACC,PER(5),R
     1(5),NDALES,WEEKST,FACT,APIK
      COMMON/HH/ DIR(25),BAS(25),NBL
      COMMON/BB/A(3,100),NS,NDAY
      COMMON/ZZ/JAY,AP1
      API(1)=AP1
2      FORMAT(8F10.3)
      WRITE(6,2) (AR(I),I=1,NA)
       DO 199 II=1,NDALES
       WEEK(II)=WEEKST
199    CONTINUE
30     II=II+1
       WEEKST=WEEKST+1
       JJ=II+6
       DO 310 K=II,JJ
       IF(K.GT.NDAY) GO TO 320
       WEEK(K)=WEEKST
310    CONTINUE
       II=K
       GO TO 30
320    CONTINUE
       TOT=0.0
       DO 321 I=1,NA
       TOT=TOT+AR(I)
321    CONTINUE
       T(1,1)=R(1)
       DO 50 I=2,NA
50     T(1,I)=0.0
       J=1
       S=0.0
4      J=J+1
       DO 51 L=1,NA
       IF(L-1) 6,6,7
6      T(J,L)=T(J-1,L)*(1.-R(L))
       GO TO 51
7      T(J,L)=(1.-R(L))*T(J-1,L)+R(L)*T(J-1,L-1)
51     CONTINUE
       S=S+T(J,NA)
       IF(S.LT.ACC) GO TO 4
       N2=J+NDN-1
       M1=NA*NDN
       DO 401 II=1,NDAY
       DO 40 MM=1,NA
       RF(MM)=0.0
       DO 40 L=1,NRG
40     RF(MM)=RF(MM)+W(MM,L)*A(L,II)
       RAN(II)=0.0
       DO 31 MM=1,NA
       RAN(II)=RAN(II)+RF(MM)*AR(MM)
```

```
31      CONTINUE
        RAN(II)=RAN(II)/TOT
        API(II+1)=API(II)*APIK+RAN(II)
        ROC=AA+BB*RAN(II)+CC*API(II)+DD*1.0+EE*WEEK(II)
        ROC=ROC*FACT
        DO 60 M=1,N2
        DO 60 N=1,M1
60      QC(M,N)=0.0
        DO 54 MM=1,NA
        N3=NDN*(MM-1)+1
        N4=N3+NDN-1
        DO 55 N=N3,N4
        N5=MM+N-N3
        N6=N5+J-MM
        LN=N-N3+1
        DO 56 M=N5,N6
        LM=M-N5+MM
        QC(M,N)=AR(MM)*PER(LN)*RF(MM)*ROC*T(LM,MM)/100.
56      CONTINUE
 55     CONTINUE
  54    CONTINUE
        DO 57 M=1,N2
        QCA(M)=0.0
        DO 57 N=1,M1
57     QCA(M)=QCA(M)+QC(M,N)
        IF(II-1) 58,58,59
58      DO 61 K=1,N2
61      QD(K)=QCA(K)
        GO TO 401
59      N7=N2-NDN
       DO 62 M=1,N7
        K=NDN*(II-1)+M
        AX=QD(K)
        BX=QCA(M)
62      QD(K)=AX+BX
        N7=N7+1
        DO 64 M=N7,N2
        K=K+1
64      QD(K)=QCA(M)
        DO 63 M=1,NDN
        KK=K+M
63      QD(KK)=0.0
401     CONTINUE
        WRITE(6,326)
326     FORMAT(//,10X,@RAINFALL@,30X,@API@,30X,@WEEK NUMBER@///)
        WRITE(6,327)(RAN(II),API(II),WEEK(II),II=1,NDAY)
327     FORMAT(10X,F8.3,27X,F8.3,30X,F8.3)
        KK=KK-NDN
       NX=KK/NDN
        N=(NX+1)*NDN-KK
        DO 41 L=1,N
        KK=KK+L
41      QD(KK)=0.0
```

```
      NX=NX+1
      DO 42 M=1,NX
      S=0.0
      N1=(M-1)*NDN+1
      N2=N1+NDN-1
      DO 43 K=N1,N2
43    S=S+QD(K)
42    QD(M)=S
      WRITE(6,999) (QD(M),M=1,NX)
999   FORMAT(///,10X,@GENERATED DIRECT DAILY RUNOFF@///,(12F11.3))
      CALL STATIC(QD,NX)
      IF(JAY.NE.1) GO TO 191
      DO 777 I=1,NX
      AS=QD(I)
      CALL BASEFL(AS)
      QD(I)=AS+QD(I)
777   CONTINUE
      WRITE(6,998) (QD(M),M=1,NX)
998   FORMAT(///,10X,@GENERATED DAILY RUNOFF WITH BASEFLOW ADDED@///,
     1 (12F11.3))
      CALL STATIC(QD,NX)
191   RETURN
      END

      SUBROUTINE STATIC(QD,NX)
      DIMENSION QD(450)
      S1=0.0
      S2=0.0
      S3=0.0
      DO 100 I=1,NX
      S1=S1+QD(I)
      S2=S2+QD(I)*QD(I)
      S3=S3+QD(I)*QD(I)*QD(I)
100   CONTINUE
      NNX=NX
      DO 200 J=1,NX
      K=NX+1-J
      IF(QD(K).GT.0.0) GO TO 300
      NNX=NNX-1
200   CONTINUE
300   A5=NNX
      A3=S1/A5
      B3=S2/(A5-1)-(S1*S1)/(A5*(A5-1))
      B3=SQRT(B3)
      G=((A5*A5)*S3-3*A5*S1*S2+2*S1*S1*S1)/
     1(A5*(A5-1)*(A5-2)*B3*B3*B3)
      WRITE(6,334)NNX,A3,B3,G
334   FORMAT(//,5X,@NUMBER OF VALUES =@,I5,5X,@MEAN =@,F15.3,5X,
     1 @STD DEV =@,F15.3,5X,@SKEWNESS =@,F15.3//)
      RETURN
      END

      SUBROUTINE BASEFL(AS)
      COMMON/HH/DIR(25),BAS(25),NBL
```

```
      DO 100 I=1,NBL
      N=NBL+1-I
      IF(AS.GT.DIR(N)) GO TO 13
100   CONTINUE
13    IF(I.NE.1) GO TO 14
      AS=DIR(N)
      DIR(N+1)=DIR(N)
      BAS(N+1)=BAS(N)
14    CONTINUE
      AS=(AS-DIR(N))*(BAS(N+1)-BAS(N))/
     1 (DIR(N+1)-DIR(N))+BAS(N)
      RETURN
      END

      SUBROUTINE GAUSSB(IX,DSTDE,DUR,V)
C     SUBROUTINE FOR RECTANGULARLY DISTRIBUTED RANDOM NUMBERS
        A=0.
        DO 50 I=1,12
        CALL RANDUM(IX,IY,Y)
        IX=IY
 50     A=A+Y
        V=(A-6.0)*DSTDE+DUR
      RETURN
      END

      SUBROUTINE RANDUM(IX,IY,YFL)
C     SUBROUTINE FOR NORMALLY  DISTRIBUTED RANDOM NUMBERS
        IY=IX*65539
        IF(IY) 5,6,6
  5     IY=IY+2147483647+1
  6     YFL=IY
        YFL=YFL*.4656613E-9
      RETURN
      END
```