CHAPTER 3

REVIEW OF LITERATURE

3.1 GENERAL

Dynamic Programming (DP) is a valuable optimization technique for water resources problems in general and the most widely used technique for optimization involving stochastic variables. The variant of DP commonly used in reservoir optimization is termed as discrete dynamic programming, since naturally existing continuous variables such as time, reservoir storage, inflows, releases and demand on the reservoir are discretized and treated as discrete variables.

DP is a mathematical solution method for optimization of multistage processes. The stages can be time periods, spatial distances etc. Normally in reservoir operation reservoir storage, soil moisture, inflow and demand etc. may be the state variables.

The concept forming the basis of DP is called the principle of optimality (Bellman, 1951):

"The optimal set of decisions in a multistage decision process has the property that whatever the initial stage, state and decisions are, the remaining decisions, given the current state in the current stage, must form a set of optimal sequence of decisions for the remaining problem".

In any DP problem the stage and the state are the frequently used terms. A stage in DP is defined as the portion of the problem that possesses a set of mutually exclusive alternatives from which the best alternative is to be selected. The definition
of the state is usually the most subtle concept in dynamic programming formulations. There is no easy way to define the state, but clues can usually be found by asking the following two questions Taha(1989).

1. What relationships bind the stages together?
2. What information is needed to make feasible decisions at the current stage without checking the feasibility of decisions made at previous stages?

The following are the typical features of every DP problem:

1. In DP problems, decisions regarding a certain problem are typically optimized at subsequent stages rather than simultaneously. This implies that if a problem is to be solved using DP, it must be separated into subproblems.

2. DP deals with problems in which choices or decisions are to be made at each stage. The set of all possible choices is reflected, governed or both by the state at each stage.

3. Associated with each decision at every stage is a return function which evaluates the choice made at each decision in terms of the contribution that the decision can make to the overall objective (maximization or minimization).

4. At each stage the total decision process is related to its adjoining stages by a quantitative relationship called a state variable transition function. The state variable transition function is the sole link between different subproblems. Since selection of states and the transition function satisfying the required DP conditions depends on the specific problem studied, DP is considered as largely an art and not primarily a science.

5. Given the current state an optimal policy for the remaining stages in terms of a possible current state is independent of the policy adopted in previous stages.
6. The solution procedure always proceeds by determining the optimal policy for each possible state at the present stage.

7. A recursive relationship is always used to relate the optimal policy at current stage and the future stages that follow. By using the recursive relation, the solution procedure move from stage to stage each time determining an optimal policy for each state at that stage until the optimal policy for the last stage is found. Once the optimal policy has been discovered, the decision vector can be recovered by tracing back through the transition functions.

Excellent review articles exist in the literature. [Yakowitz (1982): Dynamic programming applications in water resources; Yeh(1985): Reservoir operation and management models]. Use of Stochastic Dynamic Programming (SDP) for deriving optimal operating policies has become popular in recent years (e.g. Gabliger and Loucks (1970); Butcher (1971); Roefs and Guitron (1975); Stedinger et al. (1984)). The use of chance constraints in SDP have also been reported in the literature (Askew (1974a), Askew (1974b), Askew (1975), Sneidovich (1979, 1980a, 1980b).

A simple example of application of SDP for optimal reservoir operation is considered for discussing the relevant literature. Then the literature regarding Irrigation Planning Models and Realtime Operation Models for Irrigation are presented.

3.2 SDP FOR OPTIMAL RESERVOIR OPERATION

In reservoir operation one of the problems is to find out the sequence of releases that has to be made for every time period according to the state of the reservoir storage and inflow into the reservoir. The releases have to be made in such a way that the overall system performance is maximized. Figure 3.1 shows the sequential reservoir operation process. t and t+1 are time periods (DP stages). $S^t$ and $R^t$ are the reservoir storage and release during time period t. $F_t(S^t,Q^t)$ is the net benefit
that will accrue through reservoir operation from period \( t \) to the terminal period of reservoir operation process if the reservoir storage and inflow to the reservoir at time period \( t \) is \( S^t \) and \( Q^t \) respectively. The objective of optimization is to maximize the \( F_t(S^t,Q^t) \) for every time period \( t \), for every combination of possible reservoir storage \( S^t \) and inflow \( Q^t \).

3.2.1 DISCRETIZATION OF CONTINUOUS VARIABLES

For the application of discrete DP both time and volume or flow of water have to be discretized. Discretization is usually performed in a manner that leads to acceptable results, conveniently handled by an algorithm and easily understood by the analyst.

3.2.2 DISCRETIZATION OF TIME

Time is normally discretized into seasons, months or weeks for steady-state optimization. It is often customary to discretize time into equal lengths, but in many instances it is more efficient to have unequal lengths when discretizing into seasons. For example, all dry months can be discretized into one single season while other seasons may have lengths of one or two months. Figure 3.2 shows the time discretization. An year is divided into \( T \) time periods.

3.2.3 DISCRETIZATION OF VOLUME OF WATER

Volume or flow of water is discretized so that its value at any given time lies in one of several class intervals. Any value within the range of a class interval is represented by a single value for that class interval referred to as its representative value. The larger the number of such class intervals, the better the approximation of the variable. However, an increase in the number of class intervals would result in an increase in the required computer memory and run time.
FIGURE 3.1 RESERVOIR OPERATION PROCESS

FIGURE 3.2 DISCRETIZATION OF TIME
There are two commonly used approaches in discretization of reservoir storage. One is Moran (1954) scheme and another is Savareinsky’s scheme (Doran 1975). In the Moran’s scheme, the boundary storage states have class intervals of $\delta/2$ and the internal states are situated at centre points of class interval of $\delta$ covering $\delta/2$ on both the higher and lower sides. Figure 3.3a shows the Moran’s discretization scheme. In the Savareinsky’s scheme the boundary states have zero class intervals as shown in Figure 3.3b. Though the Savareinsky’s scheme is proved to be superior than the Moran’s scheme, for the discretization scheme with more than six class intervals there is no significant difference in the results (Ponnambalam 1987). While using DP the number of discretization is much larger than six, and hence either of the methods can be used.

Doran (1975) discretized the inflow and storage with the same class interval $\delta$. The release discretization was integral multiple of $\delta$. In this scheme the interpolation of the objective function during optimization is avoided saving some computing time. The disadvantage is that when $\delta$ is relatively small, a large number of discrete inflow states will be required for seasons with large inflows. Alternatively when $\delta$ is relatively large only one or two discrete states would represent the full range of inflows in dry seasons making the optimization less sensitive to inflow variability in those seasons. Klemes (1977) discretized the reservoir storage, inflow with the same class interval $\delta$ but the release was discretized in such a way that it need not be integral multiple of $\delta$. The advantage of this method over Doran (1975) is that any real value of release can be adopted thus making the model more flexible. Su and Deininger (1974) and Turgeon (1980) discretized the inflow into five class intervals in terms of the mean inflow ($\mu$) and standard deviation ($\sigma$). Su and Deininger (1974) discretized the inflow as $\mu - 2\sigma$, $\mu - \sigma$, $\mu$, $\mu + \sigma$, $\mu + 2\sigma$. Turgeon (1980) discretized as $\mu - 1.83\sigma$, $\mu - 0.89\sigma$, $\mu$, $\mu + 0.89\sigma$, $\mu + 1.83\sigma$. Wang et al (1986) also used the same scheme. Buras (1985) selected heuristically the discretization of inflows for the different seasons keeping the number of discrete states constant in each season and equal to ten.
FIGURE 3.3 RESERVOIR STORAGE DISCRETIZATION

(a) Moran's Scheme

(b) Savareisky's Scheme
Ponnambalam (1987) analyzed the effect of number of inflow discretization on the expected annual benefits. He found the number of discretization more than five do not improve the result for inflows following normal as well as skewed distributions.

### 3.2.4 STATE VARIABLES

In a hydrologic system the number of variables influencing the decision is so large that it becomes computationally impossible to consider all of them simultaneously. It is therefore necessary to choose only those variables that influence the decision process the most. For example the state vector $\Phi^t$ is defined as,

$$
\Phi^t = \{ S^t, Q^t \}
$$

where $S^t$ and $Q^t$ are defined earlier. The demand on reservoir is treated deterministic. When the serial correlation between each period is not significant, inflow $Q^t$ is not treated as state variable. Otherwise, $Q^t$ is treated as state variable. When $Q^t$ is treated as state variable inflow transition probability matrices for each period have to be constructed.

There are two commonly used methods in construction of Transition Probability Matrix (TPM). One method uses the historical data as such. However, in this method if the length of the record is small, the TPM obtained is not smooth. Buras (1985), Loftis and Houghtalan (1987) and Vedula and Mujumdar (1992) used historical data for construction of TPM.

In the other method, some marginal probability distributions are assumed for every period. The distribution parameters are estimated for every month from the historical data. Then synthetic streamflow formula is used to generate inflows for sufficiently long periods.

The transitional frequencies are computed from the transition of the inflow from each of the states at time $t$ to the same or other states at time $t+1$. Let $f_{r_{ij}}$
represent the frequency of transition from state i at time t to state j at time t+1. The transitional probability is estimated as $P_{ij} = \frac{r_{ij}}{FR_j}$.

$$FR_i = \sum_{j=1}^{N} r_{ij} \quad \text{for} \quad i=1,2,\ldots,N$$
$$FR_j = \sum_{i=1}^{N} r_{ij} \quad \text{for} \quad j=1,2,\ldots,N$$
and $N$ is number of states.

### 3.2.5 RESERVOIR STORAGE STATE TRANSFORMATION

Let the indices $i$ and $j$ represent the class intervals for the inflow, $k$ and $l$ represent the class intervals for the reservoir storage during periods $t$ and $t+1$ respectively. $S_{k}^t$, $S_{l}^{t+1}$, $Q_{i}^t$, $Q_{j}^{t+1}$ are the representative values of the state variables reservoir storage and inflow for the period $t$ and $t+1$ respectively. The reservoir storage state transformation is governed by the continuity equation

$$S_{i}^{t+1} = S_{i}^t + Q_{i}^t - R_{kil}^t - E_{kl}^t \quad \ldots \quad (3.2)$$

where $R_{kil}^t$ is the release when the storage class interval at the start of time period $t$ is $k$ and at the start of time period $t+1$ is $l$ and the inflow class interval during time period $t$ is $i$. $E_{kl}^t$ is the evaporation loss when the storage class interval at the start of time period $t$ is $k$ and at the start of time period $t+1$ is $l$. Equation 3.2 specifies the release for a given combination of $k,i$ and $l$ for every time period $t$. It is to be noted that some of the various theoretical combinations of $k,i$ and $l$ may not be feasible as they result in negative values of $R_{kil}^t$.

### 3.2.6 OBJECTIVE FUNCTION

In order to choose from among the possible values of decision variables $R_{kil}^t$, a measure of system performance has to be specified. Let the measure of system performance be $G$ and a particular value of it namely $G_{kil}^t$ be associated with release $R_{kil}^t$. The system performance measure incorporated in the objective function may be maximizing the expected benefits or simply minimizing the expected sum of squared
deviations of the release from the demand whenever it is difficult to quantify the benefits associated with the release in every period.

3.2.7 RECURSIVE RELATION

There are two ways by which recursive relations are formulated. One is forward recursive relation and another is backward recursive relation. SDP problems can be solved only by backward recursion. So backward moving dynamic programming algorithm is followed assuming that the reservoir operation terminates at some arbitrary year $Y$ in the future at the period $T$, where $T$ is the total number of periods within a year. Let $N$ be the number of periods remaining till the end of the year $Y$. Let $F^N_t(k,i)$ denote the total minimum expected value of the system performance over $N$ periods to go in the operation of the reservoir including the current period $t$ given that reservoir storage is $S^t_k$ and inflow is $Q^t_i$. Then with only one period remaining,

$$F^1_T(k,i) = \min \{ G^T_{kil} \} \forall k,i \quad (3.3)$$

where $\{1\}$ denotes feasible 1. In general for any period, $i$

$$F^N_t(k,i) = \min \{ G^t_{kil} + \sum_j P^t_{ij} F^{N-1}_{t+1}(l,j) \} \forall k,i \quad (3.4)$$

where $P^t_{ij}$ is the transition probability of inflow, defined as the probability that the inflow in period $t+1$ will be in state $j$ given that it is in state $i$ in period $t$. Equation 3.4 is solved recursively until a steady state solution is reached defining the optimal policy $l^*(k,i,t)$ for all values of $k$, $i$ and all $t$. Steady state is reached when $[F^{N+T}_t(k,i) - F^N_t(k,i)]$ becomes constant for all $k,i$ and for all $t$. 

3.2.8 DETERMINATION OF JOINT PROBABILITY DISTRIBUTION OF RESERVOIR STORAGE AND INFLOW

From the steady state optimal policy obtained from the solution of the Equations 3.3 and 3.4, the following probability distribution equations can be written.

\[ PR_{t,l}^{i,k} = \sum_i \sum_k PR_{ik}^t \cdot P_{ij}^t \quad \forall \ t, i, k \quad \ldots \ (3.5) \]

\[ \sum_i \sum_k PR_{ik}^t = 1 \quad \forall \ t \quad \ldots \ (3.6) \]

where \( PR_{ik}^t \) is the joint probability of reservoir storage \( k \) and inflow \( i \) during period \( t \). The right hand side of Equation 3.5 is a selective summation over only those initial storage and inflow indices \( k \) and \( i \) that result in a final volume having the index \( l \). In the above Equations 3.5 and 3.6, \( PR_{ik}^t \) are unknowns and \( P_{ij}^t \) are known streamflow transition probabilities. One equation in 3.5 is redundant in each period \( t \). Therefore the number of independent equations in 3.5 and 3.6 equals the number of unknowns. A unique solution can be obtained by solving those equations. The result is steady state joint probability distribution of the reservoir storage and inflow \( PR_{ik}^t \).

Using the joint probability distribution values the marginal probability distribution of reservoir storage can be obtained using Equation 3.7.

\[ PS_k^t = \sum_i PR_{ik}^t \quad \forall \ t, k \quad \ldots \ (3.7) \]

By observing the probability distribution of releases and the probability distribution of reservoir storages, alternatives can be tried by varying the reservoir capacities and/or the demand.

Loucks (1981), Buras (1985) and Goulter and Tai (1985) made use of the method discussed above for arriving at the joint probability distribution of reservoir storage and inflow. Goulter and Tai (1985) have reported that the total number of simultaneous equations obtained from Equations 3.5 and 3.6 if exceeds above 1152 it becomes computationally impossible to solve.
Loucks (1968) applied stochastic linear programming to obtain the joint probability distribution of reservoir storage and inflow under optimal operating conditions. Later Loucks et al. (1981), found that the result obtained through this method and the method mentioned above give the same results. But since the stochastic linear programming suffers severely from dimensionality problem than the method discussed above, it is not in use at present. Ponnambalam (1987) used simulation of steady state optimal policy obtained from application of SDP using historical data to obtain the probability distributions. This method does not suffer from any dimensionality problem.

### 3.3 PLANNING MODELS FOR IRRIGATION

Dudley along with many co-authors has published series of papers in Irrigation Planning. Dudley et al. (1971a) analyzed the short term problem of irrigation scheduling using simulation and SDP. Two state variables namely soil water content and terminal soil moisture level (i.e., the level to which soil moisture can be allowed to fall before irrigation is initiated to return the soil to field capacity) are used. The state variable transition probabilities are generated by simulating plant growth under conditions determined by historical rainfall and evaporation data. The medium term problem, that of deciding the extent of area of crop to plant at the beginning of an irrigation season using the results obtained from the short term model was analyzed by Dudley et al. (1971b). Dudley et al. (1972a) analyzed the long term problem of sizing the irrigation area to be developed for a given reservoir capacity. Dudley (1972b) developed SDP to estimate the expected benefits from allocating water optimally between seasons. They simulated the results for number of seasons and found that interseasonal transfer can considerably increase the present value of the expected benefits. Some of the limitations noted in the above works of Dudley et al. are as follows: (i) the plant growth in one stage is independent of the growth in the previous stages, (ii) the crop has zero growth on the days it is stressed, irrespective of the magnitude of the stress, (iii) only one crop is assumed to be grown in the command area, (iv) the serial correlations for inflow into reservoir and rainfall are not considered.
Dudley et al. (1973) attempted to solve the scheduling problem as a part of the overall system design. They sought to solve the design and planning problem of determining (i) the optimal reservoir capacity, (ii) the acreage to be developed for irrigation, and (iii) the distribution capacity of the system. Most of their effort was spent in solving the scheduling problem and quantifying the trade off between mean and variance of benefits. It was suggested that these measures could be used by the decision maker to answer the original design problem. A dynamic programming model was developed originally with four state variables and two decision variables. The state variables are (i) percentage of available soil moisture (one variable for all farms), (ii) reservoir storage level, (iii) acreages available for irrigations (as stages grow forward this variable can be the same or less, but never more than the previous stage value), and (iv) a crop production function that depends on climatic and cultural variables as well as soil moisture. The decision variables are (i) the terminal soil moisture level to indicate when irrigation should be practised to bring the soil to its field capacity and (ii) the acreage irrigated (which should always be less than or equal to the third state variable mentioned above). Although the above model was developed, it was never applied in that form. It was changed to a relatively simpler model to make the problem solution computationally feasible. The simpler version contained the first three state variables and both the decision variables. A discount factor was employed in the dynamic programming model. Limiting probability distributions were calculated and used to determine the asymptotic mean and variance of expected net benefits. Dudley et al. (1976) used the above model to aid in management and planning decisions for multicrop water resource systems located in fairly humid regions. Although they solved a multicrop problem, only deterministic water demands were considered. Dudley (1988) refined his earlier works by incorporating a complex soil water-plant growth simulation model for cotton and simulated the effects of using optimal decisions derived by SDP.

Dudley has shown in many of his papers, even a single reservoir problem is computationally very intensive and is difficult to solve due to (i) difficulty in realistically modelling crop-growth function, (ii) difficulty in knowing rewards, (iii)
water demands being difficult to estimate and once estimated usually are highly stochastic. These difficulties are in addition to the ones usually encountered in reservoir operation problems such as stochastic inflows and curse of dimensionality and so on.

Vedula and Mujumdar (1992a) developed a three state Stochastic Dynamic Programming (SDP) model to derive steady state operating policy for irrigation under multiple crops scenario. The crop types, crop calendar and the area of cropping were assumed identical for every year. Mujumdar and Vedula (1992b) evaluated the performance of an irrigation system with multiple crops under three different optimal operating policies derived through SDP. In policy I the objective function minimizes the expected sum of squared deviations of release from crop demand. Two state variables namely reservoir storage and inflow were considered. The crop demand was considered deterministic. The soil moisture contribution to meet the crop demand was not considered. Policy II accounts for soil moisture contribution to meet the crop demand by incorporating soil moisture as a third state variable. The release from the reservoir was divided according to the demand of each crop. Policy II was considered to be an improvement over the policy I. In policy III, when competition for water exists among crops, the allocation for individual crops was done through an optimization model which forms part of the SDP model that determines the optimal release policy. This is conceptually an improvement over policy II wherein the allocation for individual crops was in proportion to each crop demand. It was found that the policy II performed well compared to policy I and policy III.

From the above two works it can be concluded that the integrated development of the model for optimal allocation of water for individual crops treating stochastic supply and demand with dynamic soil moisture accounting for multiple crops scenario is still a formidable problem.
3.4 REALTIME OPERATION MODELS FOR IRRIGATION

Palmer-Jones (1977) used SDP to determine optimal irrigation policies for mature tea (deep rooted crop) in Malawi. He found that two or more state variables are necessary to realistically represent the soil moisture variation at different depths. He considered the serial correlation of river inflows unlike all the Dudley et al's works and found that the improvement in expected returns due to considering serial correlation of flows is significant.

Bras and Cordova (1981) developed SDP model for optimal temporal allocation of irrigation water, taking into consideration the intraseasonal stochastic variation of the crop water requirements and the dynamics of the soil moisture depletion process. In this work, the soil moisture transition probabilities are derived analytically whereas in all the preceding works simulation is used to derive transition probabilities.

Rhenals and Bras (1981) developed SDP model by considering the potential evapotranspiration as state variable in order to consider the natural uncertainty in potential evapotranspiration. They compared the results with deterministic treatment of potential evapotranspiration and found that the difference due to considering uncertain potential evapotranspiration is insignificant for their selected case study.

Loftis and Houghtalan (1987) developed SDP model to optimally allocate irrigation water for a crop season considering rainfall and inflow into reservoir to be deterministic and potential evapotranspiration to be stochastic. They used minimizing the expected sum of squared deviations as the objective function whereas in all the preceding works related to optimizing irrigation systems maximizing expected returns or yield is the objective function. They substantiated the use of sum of squared deviations as objective function and reported as follows:
Since most of the yield models which have been suggested for irrigation are at least partly empirical, a large cost is incurred for local calibration over a reasonable number of years. To date these models have not demonstrated the precision and portability necessary for application in economic optimization of irrigation systems unless one is willing to assume considerable risk associated with yield model uncertainty. All the yield models require accurate estimation of soil moisture on a field scale and estimation on large scale would be impractical.

They compared the stochastic treatment of potential evapotranspiration with deterministic treatment and found that the stochastic approach always outperforming deterministic approach.

Houghtalan and Loftis (1988) developed Aggregate State Dynamic Programming (ASDP) for multiple reservoir systems taking crop demand and water supply to be stochastic. The spatial allocation of water among different reservoirs is based on heuristic rules. The total available water for irrigation in all the reservoirs is treated as state variable. Houghtalan and Loftis (1990) improved their earlier work by incorporating an interactive simulator with the ASDP model. By doing several trials of reservoir operations with different set of heuristic rules to allocate water spatially among different reservoirs, they found that it was possible to improve the quality of heuristic rules.

Wang and Adams (1986) solved the reservoir operation problem in two phases which consists of a real time model followed by a steady state model. The steady state model (Phase II) is solved with out considering the serial correlation of inflows and treating the reservoir storage alone as the state variable. From the steady state model the boundary values of every storage state for every period are obtained. These results are used as the boundary condition for the real time operation model (Phase I). The real time optimal operating policy is conditioned upon the preceding period inflow and the current period storage. By this two phase frame work they found that the computational efficiency obtained is significant. Their view point is that the
periods in Phase II are far enough from the Phase I such that the prospective operations occurring in Phase II are not significantly influenced by the Phase I conditions and Phase II is hence defined as the steady state operation periods. When examined from the viewpoint of Phase I the prospective inflow distributions in Phase II will converge to their respective monthly limiting distributions regardless of the actual inflow in the previous time period. They have attributed this reason for not considering the serial correlation between inflows.

Ponnambalam (1987) developed three stage framework for optimal reservoir operation. This approach is similar to the Wang et al (1986) approach. In this approach real-time horizon is 14 days. The total number of periods considered for real-time operation is eight with 1 day as the time interval for the first week and the eighth period with one week. The real-time operation model uses meteorological forecasts data such as rainfall, inflow and potential evapotranspiration. The boundary values for real-term optimization is mid-term optimization and the time interval for mid-term optimization is a week and the time horizon is for two crop seasons. The boundary values for mid-term optimization is steady-state optimization with time interval of one month.

Kuo et al (1990) developed a real-time operation modelling package for a selected case study. The package consists of streamflow forecast model, a rule curve based simulation model and an optimization model. Given a forecasted streamflow sequence for the entire year, the simulation model is first used to determine whether a severe shortage of water is expected. Using the simulation results as an initial feasible operating policy a dynamic programming based optimization model is then used to determine an improved operating policy. At the end of each 10 day period the streamflow forecast is updated and the simulation and optimization models are rerun for remaining periods of the year. The cycle is repeated until the last period is reached. Rao (1985) also used similar approach.

Vedula and Mohan (1990) developed a real-time operation methodology for a multipurpose reservoir problem. They adopted SDP to derive optimal release policy. The optimal policy is conditioned upon current storage and inflow in the current
period. In order to be able to use the policy for real time operation of the reservoir, knowledge of current period inflow for each period is essential. To circumvent this, Loucks et al (1981) proposed a methodology to derive an optimal steady state policy that does not depend on the inflow of the current period by identifying either a final storage volume target subject to limitations on the releases or reservoir releases subject to limitations on final storage volumes. However Vedula and Mohan (1990) have used an adaptive AutoRegressive Integrated Moving Average model to forecast current period’s inflow.

3.5 SCOPE AND OBJECTIVES OF THE STUDY

From studying the existing reservoir operation practice, cropping pattern in the study area and other characteristics and also from reviewing the literature following objectives were framed for this Thesis Work.

1. To develop an optimization model for operation of irrigation systems wherein tanks exist in the command area and apply the model to KRP.

2. The steady-state models developed so far consider a fixed crop area and calendar every year. In many irrigation systems in South India because of high variability in inflows from year to year the cropping pattern is decided based on the storage available at the start of every season. So the cropping pattern does not remain the same every year and its variability adds one more dimension in developing the SDP model. SDP model for this is to be developed and applied to KRP and the usefulness of the model is to be evaluated.

3. To develop a SDP model treating the inflow into reservoir as independent for the periods for which the serial correlation coefficient is statistically insignificant and as first order Markovian for the periods for which the serial correlation is statistically significant in order to reduce the problem of dimensionality. To apply the model to KRP and to evaluate the results obtained from the model.