RESERVOIR OPERATION CONSIDERING DOWNSTREAM IMPACT OF A HYDROELECTRIC PROJECT

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By

Maya Rajnarayan Ray

Department of Civil Engineering
Indian Institute of Technology Guwahati,
Guwahati-781039, INDIA

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Dedicated To My Parents, Husband and Guruji

DEPARTMENT OF CIVIL ENGINEERING
Indian Institute of Technology, Guwahati

Guwahati-781039, Assam, INDIA
Fax: +91 361 2582440
E-mail: r.ray@iitg.ernet.in

Date: 27th December 2010

STATEMENT

The work contained in the thesis entitled "**RESERVOIR OPERATION CONSIDERING DOWNSTREAM IMPACT OF A HYDROELECTRIC PROJECT**" has been carried out by me under supervision of **Prof. A. K. Sarma**, Department of Civil Engineering, Indian Institute of Technology Guwahati. This work has not been submitted elsewhere for the award of any degree.

Maya Rajnarayan Ray
Research Scholar (Roll No: 06610407)
Department of Civil Engineering
Indian Institute of Technology Guwahati
Assam – 781039 (Guwahati).

Prof. A. K. Sarma
B.P.Chaliha Chair Professor for Water Resources

Indian Institute of Technology Guwahati,
Guwahati-781 039

Phones: 0361- 2582409 (O)
0361- 2584409 (R)
0361- 2690953 (R)
Fax: 0361- 2582440
E-mail: aks@iitg.ernet.in

DEPARTMENT OF CIVIL ENGINEERING

Date: 27th December 2010

Certificate

*It is certified that the work contained in the thesis entitled "**RESERVOIR OPERATION CONSIDERING DOWNSTREAM IMPACT OF A HYDROELECTRIC PROJECT**" by Maya Rajnarayan Ray, Roll Number 06610407, a student in the Department of Civil Engineering, Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.*

(Arup Kumar Sarma)

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ABSTRACT

With the increasing demand of power, hydropower projects are coming up at a much faster rate in the developing countries of the world. These projects are generally operated to meet the power demand during peak hours, which induces significant diurnal variations downstream of the dam. Such dam-induced diurnal variations may lead to many adverse impacts downstream. Upstream impacts are quite obvious getting more attention from the scientific community; whereas downstream impacts, which are not visible immediately after the dam construction or seen quite far downstream from the dam site, hardly get proper attention. Therefore, an effort is being made in this study to address such impacts and to quantify the consequent losses, so that such hydropower projects can be designed and operated to have optimal benefit considering power need and giving due emphasis to the water requirement of downstream habitats.

The concepts developed in this study has been applied to Lower Subansiri Hydro Electric(LSHE) project located on the River Subansiri, a major tributary of river Brahmaputra. The primary objective of this project is to generate 2000 MW hydropower for meeting power demand during peak hour. As majority of population downstream of LSHE project depends upon the agriculture and fishery, an attempt has been made for quantifications of downstream losses giving more emphasis on these two aspects.

LSHE project considered in the present study has limited historical streamflow data. As such, this data set is not adequate to develop a generalized optimal operating policy. Hence synthetic steamflow series are generated for different time steps using Thomas -Fiering and

ANN models. It was found from the study that synthetic streamflow generated by Thomas-Fiering model was performing better in lean period while ANN model was performing better in wet season. Therefore using capability of both models, a hybrid model is developed for the generation of synthetic streamflow for ten day time step, to develop a ten day optimal operating policy. The reservoir simulation model is developed for visualizing post operational flow scenario of the dam. The simulation study has revealed that, with the proposed power production schedule, i.e. with peaking hour of minimum 4 hours, the downstream flow will be varying with a diurnal variation between $6m^3/s$ to $2500m^3/s$ in the lean period while natural flow in river Subansiri in lean period is in the order of $500m^3/s$. Such diurnal variation in the streamflow will have adverse ecological effects. To minimize such diurnal variations, structural measure, i.e. introducing regulating pond at immediate downstream of the dam and non-structural measures, i.e. changing operating schedule, have been attempted. Comparisons have revealed that structural measure provides the best solution which gives maximum benefit without compromise in peaking hours of power generation, but its implementation depends on many factors like availability of suitable site, availability of fund to meet initial investment and the maintenance cost. Non-structural measure-I i.e. operating one turbine continuously and rest of the turbines simultaneously, has also been found to provide notable improvements over the baseline standard operation scenario. Besides these measures for minimizing diurnal variations, a deterministic dynamic programming approach for maximization of net benefits considering different losses downstream due to operation of hydropower project has also been developed. Dynamic Programming with multiple linear regression (DPR) approach has been used to infer the general optimal operating policy (GOOP). The comparison of GOOP is made with the standard operating policy (SOP). It has been found from the result that annual net benefit obtained using GOOPs are high as compared to SOPs, of course with the compromise in annual power production. All these proposed operating policies have been compared using seven performance criteria, namely; Net benefit (₹), Average Annual Power Production (MU), Minimum Peaking Hour per day, Minimum Downstream Flow (m^3/s), Probability (%) of failure to meet the 4 hours peaking requirements, Maximum deficit in annual target power production (MU) and percentage of maximum deficit in annual target power production. Considering overall performance and need of meeting peaking hour power requirement as well as downstream environmental flow, structural measure has been found to be the best. GOOP1 can be given second preference while non-structural measure–I can be preferred when continuous power production throughout the year is required.

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a_1, a_2 and a_3	= Coefficients of the regression equation developed for general operating policy
A_t	= Area of reservoir in Ha
b_j	= Bias for the j^{th} neuron in the hidden layer
C_{Kd}	= Downstream channel capacity
DP	=Deep percolation (mm)
El_{nt}	=Elevation of reservoir at the end of time t (m)
El_t	=Elevation of reservoir at the beginning of time t (m)
El_{tail}	=Elevation of normal tail race water (m)
ER	= Effective rainfall (mm)
E_t	= Evaporation at time t (Mm^3)
ET_{crop}	= Crop water need (mm/day)
ET_a	= Actual evapotranspiration (mm/day)
ET_m	= Maximum crop evapotranspiration
ET_o	= Reference crop evapotranspiration (mm/day) as an average for a period of 1 month
T_{mean}	= Mean daily temperature (°C)
P	= Mean daily percentage of annual daytime hours
f	= Activation function
g	= Gravitational acceleration (9.81) m/s^2
G_{t+1}	=Average time rate of change of discharge of the series
h_f	= Head loss due to friction (m) corresponding to El_t and El_n
H_n	= Net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at beginning of time t (m)
H_{nn}	= New net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at end of time t (m)
H_{nt}	= Net Head (m) at any time t (m)
H_r	= Duration of turbine operation (hour)
$I_{p,\ t+1}$	= Predicted inflow at time t+1(m^3/s)
IR	= Irrigation requirement (mm)
I_t	= Inflow at time t (Mm^3)
I_{t-1}	= Streamflow of previous period

K_c	= Crop factor which depend on type of crop, growth stage of crop and climate
K_{El}	= Storage capacity (Mm^3) of reservoir at time t
K_y	= Yield response factor
L_{fat}	= Loss of agriculture at downstream due to water scarcity
L_{fft}	= Ten daily fish production (kg) for time t
L_{fpt}	= Loss of fish production at downstream due to water scarcity
max_{t+1}	= Maximum value of inflow from the given historical record
min_{t+1}	= Minimum value of inflow from the given historical record
n	= Total number of time periods remaining including the current period before
net_j	= Weighted sum of input into the neuron j
p	= Period which may be of any length say 10 days or month
p	= Total number of training pattern
P	= Power (W) i.e 2000×10^6 W
P_{bit}	= Profit from power production during time period t
p_k	= Peeking hour *(h)*
q	= Number of neurons in the output layer
q	= Number of output nodes
Q_1	= Discharge (m^3/s) required to produce 2000MW power
Q_2	= Discharge (m^3/s) passing through penstocks
$q_{av,p}$	= Mean of the historical streamflow series for period p(current period)
$q_{av,p+1}$	= Mean of the historical streamflow series for period $p+1$(next period)
Q_{dt}	= Discharge passing through turbines m^3/s for time t
Q_{nt}	= Discharge (m^3/s) in non operating hour after the dam construction time t
$q_{p+1,t}$	= Logarithmic predicted value of period $p+1$ for a particular t
Q_t	= Natural discharge (m^3/s) before dam construction
R_f	= Cost of fish per kg (Rs)
R_m	= Minimum mandatory release (Mm^3)
R_t	= Release at time t (Mm^3)
R_{ta}	= Available release (Mm^3)
R_{td}	`= Minimum desired release (Mm^3)

R_{tdm}	= Minimum downstream environment release (Mm^3)
R_{tm}	=Maximum release (Mm^3) for any time t
R_{tmax}	= Maximum release in time t
R_{tmin}	= Minimum release in time t
s	= Epoch/training iteration number
S_d	= Storage capacity of the reservoir at MDDL = dead storage volume = 720 (Mm^3)
S_{max}	= Storage capacity of reservoir at FRL =1365 (Mm^3)
S_t	= Reservoir storage (a state variable) at the beginning of time period t (Mm^3)
S_{t+1}	= Storage in Mm^3 at the end of the time period t or beginning of time period $t+1$
t	= Index of time period (10 days)
TDF	= Total downstream flow (Mm^3)
w_{ji}	= Weight of the connection joining the j^{th} neuron in the hidden layer with the i^{t} neuron in the input layer
w_t	= Weightage factor that depends on fish variety and season
x_i	= The value of the i^{th} neuron in the input layer
Y	= n (n =1,2,3,4..........3600)
Y_a	= Actual yield
y_j	= Output from the j^{th} neuron in the hidden layer
$y_j^{(t)}$	= Standardized target value for pattern j
Y_{max}	= Maximum yield
α	= Momentum factor
δ	= Factor depending on whether neuron j is an output neuron or a hidden neuron
δ_q	= Computed for the q^{th} neuron in the output layer
η	= Combined efficiency of turbine and generator in percent in % (0.9)
η	= Learning rate
μ_{t+1}	= Mean of the historical streamflow of next period t+1
$\xi_{p,t}$	= Independent standard normal random variable
ρ	= Density (kg/m^3) ($\sim 1000\ kg/m^3$ for water)
σ_p and σ_{p+1}	= Standard deviation of historical series of period p and $p+1$ respectively
$r_{p,p+1}$	= Correlation between period p and $p+1$ of historical series
σ_{t+1}	= Standard deviation of historical streamflow of next period t+1

φ_t	= Discrete set of characteristic storage volumes considered at the beginning of time period t
ΔW	=Change in soil moisture (mm)
₹	=Symbol of Indian Rupees

List of Abbreviations

ACO	Ant Colony Algorithm
AI	Artificial Intelligence
ANFIS	Adaptive Network-Based Fuzzy Inference System
ANN	Artificial Neural Network
ANN 10D	ANN model for ten daily streamflow generation
ANN01D	ANN model for daily streamflow generation
ANN01D1	ANN model for daily streamflow generation with: I_t, μ_{t+1} and σ_{t+1} input parameters
ANN01D2	ANN model for daily streamflow generation with: I_{t-1}, μ_{t+1} and σ_{t+1} input parameters
ANN01D3	ANN model for daily streamflow generation with: I_t, μ_{t+1}, σ_{t+1} and G_{t+1} input parameters
ANN01D4	ANN model for daily streamflow generation with: I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1} input parameters
ANN01D5	ANN model for daily streamflow generation with: I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1} input parameters
ANN01D6	ANN model for daily streamflow generation with: I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and G_{t+1} input parameters
ANN01D7	ANN model for daily streamflow generation with: I_{t-1}, I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and G_{t+1} input parameters
ANN05D	ANN model for five daily streamflow generation
ANN06D	ANN model for six daily streamflow generation
ANN08D	ANN model for eight daily streamflow generation
ANN30D	ANN model for monthly streamflow generation
AR	Auto-regressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BCDC	Ben Chifley Dam Catchments

BP	Back Propagation
CCANN	Cascade Correlation Artificial Neural Network
CEA	Central Electricity Authority
CG	Conjugate Gradient
CROPWAT	Decision support tool developed by the Land and Water Development Division of FAO
CVP	Central Valley Project
DDDP	Discrete Differential DP
DDSP	Demand Driven Stochastic Dynamic Programming
DEQ	Department of Environmental Quality
DM	Decision Maker's
DOC	Dissolved Organic Carbon
DP	Dynamic Programming
DPR	Multiple Linear Regressions
DSM	Decision Support Model
EL	Elevation Level
ESP	Ensemble Streamflow Prediction
FAO	Food and Agriculture Organization
FDP	Folded dynamic programming
FR	Fuzzy Regression
FRL	Full Reservoir Level
FSDP	Fuzzy -State Stochastic Dynamic Programming
GA	Genetic Algorithms
GIS	Geographical Information System
GOOP	General Optimal Operating Policy
GOOP1	The GOOP developed with only 6 m^3/s discharge in non-operating hours
GOOP2	The GOOP developed with only 6 m^3/s discharge in non-operating hours
GRG	Generalized reduced gradient
GRG2	Generalized reduced gradient code
IDP	Incremental DP
IS	Indian Standard

ISDP	Incremental sequential dynamic programming
ISO	Implicit Stochastic Optimization
kWh	Kilo Watt-Hour
LANDSAT	Land Remote-Sensing Satellite
LDR	Linear Decision Rule
L-M	Levenberg-Marquardt
LP	Linear Programming
LSHE	Lower Subansiri Hydro Electric
MAE	Mean Absolute Error
MDDL	Maximum Draw Down Level
MLP	Multi-Layer Perceptron
MLP-ANN	Multilayer Perceptron Artificial Neural Network
MOM	Method of Multipliers
MRE	Mean Relative Error
MRL	Minimum Reservoir Level
MSE	Mean Square Error
MU	Million Units
MW	Mega watt
MWL	Maximum Water Level
NHPC	National HydroPower Corporation
NLP	Nonlinear Programming
NN	Neural Network
NO_3	Nitrate
PO_4	Phosphate
PRR	Project River Recovery
RL	Reduced Level
RMSE	Relative Mean Square Error
RoR	Run-off-the -river
RSM	Reservoir Simulation Model
SDP	Stochastic dynamic programming
SIDP	State-Incremental Dynamic Programming

SLP	Sequential Linear Programming-
SNP	Seminonparametric
SO_4	Sulphate
SOP	Standard Operating Policy
SOP1	The SOP developed with only 250 m^3/s discharge in non-operating hours
SOP2	The SOP developed with only 6 m^3/s discharge in non-operating hours
SQP	Sequential Quadratic Programming
SSDP	Sampling Stochastic Dynamic Programming
TDF	Total Downstream Flow
TDN	Total Dissolved Nitrogen
TSS	Total Suspended Solids
WDS	Water Distribution Systems
WESTEX	Water Quality Simulation Model
WQ	Water Quality
WRS	Water Resources System

Chapter 1

Introduction

1.1 Purpose of the Study

India is blessed by enormous hydropower potential which can be economically harnessed from Brahamaputra, Indus and Ganges basins. Out of such a huge hydro power potential, on an average 15 percent is utilized so far whereas another 7 percent is under different stages of development (CEA 2001). In India Northeastern region is identified as a region of highest hydropower potential. About 168 hydropower projects having a power potential of nearly 63,628MW have been identified in Brahmaputra river basin alone including 22 projects of about 15,191 MW potential in Subansiri river basin (CEA 2001). Out of such a huge hydro power potential of Subansiri river basin only 7 percent is developed and utilized so far and the remaining 93 percent is yet to be utilized (CEA 2001). Proper development of these available water resources is essential for prosperity of the nation.

Although construction of dam provides lots of benefits like power, irrigation, agriculture and flood moderation, it can induce some environmental problems both at upstream and downstream of the dam because of flow augmentation. Following are some of the adverse impacts that a dam can have on the environment and ecosystem:

1. Loss of habitat and many important natural resources due to submergence of land and forest upstream.
2. Disturbances caused to the people residing upstream and downstream of the dam in terms of displacement, the availability of natural flow and change of livelihood.
3. Changes in downstream morphology of riverbed, delta and bank-line due to altered sediment load leading to increased erosion.

4. Changes in downstream water quality due to change in river temperature, nutrient load, turbidity, dissolved gases, concentration of heavy metals and minerals.
5. Reduction in biodiversity because of above changes and also due to blockage of movement of river biota.
6. Changes in flow regime downstream
   a) Change in seasonal flows in case of storage dam.
   b) Diurnal variation due to turbine operation in case of hydroelectric project operated as peaking power plant.
   c) Change in extreme high and low flows.

As upstream impacts are quite obvious, getting more attention from scientific, social and political community, downstream impacts hardly get wide attention as these impacts are not noticeably striking immediately after the dam construction. It has been realized over the years that these adverse impacts of downstream can be minimized both by proper operation of reservoir and compromising with some of the objectives. Run-of-the-river projects are generally considered as having less impact on environment. However, hydropower project developed for producing power during peak hour of the day may induce significant diurnal variation at the downstream depending on the pondage provision and installation capacity. Such diurnal variation can have several adverse impacts on the downstream environment. Therefore, in this study an attempt has been made to develop an optimal operating policy for hydropower reservoir giving due consideration towards minimization of downstream impacts. Again, non-availability of long series of historical streamflow data becomes a constraint in developing reservoir operating policy. In this backdrop, it becomes necessary to develop synthetic streamflow series for deriving operating policy with more confidence. In this study an attempt has also been made to develop an ANN based models capable of generating synthetic streamflow with smaller time step discretization.

To have a detailed investigation, the Lower Subansiri Hydro Electric (LSHE) project, which is under development stage, is considered for the study. The LSHE project is a hydropower project situated on the river Subansiri, a major tributary of river Brahmaputra bwhich contributes 10 percent of the flow of River Brahmaputra calculated at Pandu. The primary objective of this reservoir is to generate power. However, this can also be operated to attenuate storm induced flood peak to some extent, provided a system of forecasting inflow to the reservoir is established.

Therefore, objectives of this study are;

a) Assessment of diurnal variation and scope of mitigating its adverse impact downstream.
b) Analysis of downstream impacts and development of an approach for quantification of some of the significant losses.
c) Generating synthetic streamflow series for deriving optimal operating policy.
d) Development of optimal operating policy for maximizing total benefit.

1.2 Method of Investigation

Development of optimal operating policy has been an active area of research for scientific community during the last four decades. Developing an optimal operating policy with environmental constraints is a challenging task. Significant research has also been done in the past towards synthetic streamflow generation. Therefore, to know the present state of-the- art, a detail review of the previous work done in different topics related to this study, is first carried out in a systematic way and presented in chapter 2.

An overview of the LSHE project, its climatic condition and principal features of the proposed multipurpose project has been presented in the chapter 3.

Giving due attention to the possible environmental impact and consequent losses occurred downstream due to operation of the hydro power project, the chapter 4 is dedicated to the downstream impact. Here an attempt has been made to analyze the possible losses in a hydropower project and to derive loss function for two major losses.

Understanding of the reservoir system in a proper manner is essential before applying any optimization method to derive an optimal operating policy. Mathematical formulation of the problem demands consideration of various aspects of the project. Details of problem formulation are presented in the chapter 5.

For any project having a short available data series, it becomes essential to generate a long series of data for the study of the reservoir operation. Hence the chapter 6 comprises the synthetic streamflow generation using different methods. Special attention is being given to study the influence of time step discretization on the synthetic stream flow generation.

Simulation is an important tool to visualize the behavior of the system in a batter way using a set of mathematical equations. In this study an attempt has been made to simulate the reservoir operation phenomenon for different operating policies. The main purpose of the simulation study conducted in this research work is to get an idea about the diurnal variations occurring in the downstream of the dam due to operation of hydroelectric project. Reservoir Simulation Model (RSM) developed for the purpose and details of alternate scenario simulated is presented in chapter 7. Scope of minimizing diurnal variation through structural and non structural measures has also been investigated by applying the simulation model developed in this chapter.

Chapter 8 presents the development of optimal operating policy for the LSHE project using deterministic dynamic programming approach. The deterministic dynamic programming has been solved for maximization of net benefits considering different losses downstream due to hydro power project. The multiple linear regression approach has been used to infer the general optimal operating policy.

Critical evaluation of the standard operating policy and optimal operating policy considering downstream losses has been carried out in chapter 9.

Chapter 10, the concluding chapter, deals with a comprehensive conclusion and general discussion on the works carried out. A guideline towards the scope of further study has also been laid down in this concluding chapter.

1.3 Conclusion

Potential of hydropower production is highest in the Northeastern part of the India. So, it is necessary to develop this resource to meet the increasing demand for the power. On the other hand, the development of major hydropower project always faces objections from various corners as it induces some environmental disturbances. A sincere attempt has been made to address this issue so that a logical compromise between development and conservation can be made through proper scientific analysis. Effort will be made to derive an optimal operating policy so that overall benefit from a reservoir can be maximized by giving due emphasis on the environmental issues.

Chapter 2

Literature Review

2.1 Introduction

The chapter presents a review of previous works on different topics that are available in literature and are closely related to the proposed research work.

Studies carried out by different investigators on different topics are presented under different subheadings. Focus of this study being reservoir operation, giving due emphasis on its downstream impact, available literature on downstream impact of reservoir has been reviewed first. Various studies conducted on reservoir operation have then been presented. Non availability of long series of streamflow generally demands synthetic streamflow generation. Therefore, available literature on steamflow generation has also been studied with due importance.

2.2 Review of Previous works on Downstream Impact

Although construction of dam provides lots of benefits like power, irrigation, agriculture and flood moderation, it may induce some environmental problems both at upstream and downstream of the dam because of flow augmentation. As upstream impacts are quite obvious they get more attention from scientific, social and political community. Whereas downstream impacts hardly get wide attention as these impacts are not noticeable immediately after the dam construction. During the last decade downstream impact of reservoir operation has drawn interest among scientific community. A systematic review of the studies, carried out on downstream impacts by different researchers, is presented in this section.

Scudder's (1980) gave the idea about the coordination of reservoir releases to maximize reservoir drawdown agriculture and downstream flood farming instead of hydroelectric power output or intensive irrigation.

Adams et al. (1986) presented that the dam construction can have significant effects on downstream floodplain environments in tropical Africa, the Tana River Valley in Kenya and in the Sokoto River Valley in Nigeria. They described the downstream impacts in those case studies and the implications of that for environmental appraisal in project planning were also assessed. They concluded that in most cases environmental provisions are simply grafted onto an existing project appraisal system as an afterthought or as an extra. Project planning is dominated by certain disciplines (particularly economics and engineering), and often steamrollered by pressing political factors of one sort or another. Environmental appraisal is peripheral to this process, and simply expanding it and improving internal procedures will itself make no difference to that peripheral position.

Dionne and Therien (1997) proposed a generic differential mass balance model for the calculation of the concentration of material released into the water column from inundated vegetation and soils as a function of several operational scenarios for the filling and emptying of reservoirs. They found that the maximum surface area of the land flooded, the maximum volume of water in the reservoir and the annual average turbine flow rate were strongly correlated. Model application had checked considering explicitly the characteristics of influent volumetric flow rate, water temperature and densities of the inundated phytomass and soils at specific latitude and the respective kinetics for the release of material into the water column. The results have indicated that the optimum times to initiate the filling operation and to initiate the subsequent emptying of the reservoir are relatively insensitive to parameters such as the residual volume of water in the reservoir and the residency time of the water in the reservoir. Also, these optimum operational parameters were found relatively insensitive to water temperature of the reservoir, influent volumetric flow rates or densities of the vegetation and soil components at the latitude at which a reservoir is sited. The integral of concentration of organic Carbon was taken as a representative measure of the environmental impact in their study.

Kondolf (1997) presented a study on sediment transport from eroding uplands to depositional areas near sea level. If the continuity of sediment transport is interrupted by dams or removal of sediment from the channel bed occurs due to gravel mining, the flow may become sediment-starved (hungry water) and prone to erode the channel bed and banks, producing channel incision (downcutting), coarsening of bed material, and loss of spawning gravels for salmon and trout (as smaller gravels are transported without replacement from upstream). Gravel was artificially added to the River Rhine to prevent further inci- sion and to many other rivers in attempts to restore spawning habitat. It is possible to pass incoming sediment through some small reservoirs, thereby maintaining the continuity of sediment transport through the system. Damming and mining have reduced sediment delivery from rivers to many coastal areas, leading to accelerated beach erosion. Sand and gravel mined for construction are aggregate from river channel and floodplains. In-channel mining commonly causes incision, which may propagate up- and downstream of the mine, undermining bridges, inducing channel instability, and lowering alluvial water tables. Floodplain gravel pits have the potential to become wildlife habitat upon reclamation, but may be captured by the active channel and thereby become instream pits. Management of sand and gravel in rivers must be done on a regional basis, restoring the continuity of sediment transport wherever possible and encouraging alternatives to river-derived aggregate sources.

Graf (2001) revealed that installation of more than 80,000 dams in America has segmented the streams and fragmented their watersheds. Physical integrity for rivers refers to a set of active fluvial processes and landforms wherein the channel, near-channel landforms, sediments, and overall river configuration maintain a dynamic equilibrium, with adjustments not exceeding limits of change defined by societal values. Rivers with physical integrity have functional surfaces and materials that are susceptible to monitoring and measurement with a set of geographic indicator parameters. The dams that fragment the system also offer opportunities for restoration of some natural characteristics through adjusted operating rules, redesign, and physical renovation, along with the removal of some dysfunctional structures. In the near future, when social values for rivers are likely to revolve around protection for endangered species, economics of flood protection, and dam removal issues, we can enhance restoration efforts by including physical integrity in research agendas, policy decisions, operational rulemaking, and public debate.

Chen (2002) presented a study on impact of dam on fisheries. He stated that worldwide, approximately 40% of the fresh water and particulate matter entering the oceans is transported by the ten largest rivers, and this is in the form of a buoyant plume or feather-like formation on the open shelves. These shelves face diminished fish production when damming reduces freshwater outflow and the buoyancy effect.

Newham et al. (2003) introduced an integrated hydrologic, stream sediment and nutrient export modeling system, which simulate catchments-scale land and water management activities. The model is applied to Ben Chifley Dam Catchments BCDC of Australia. To examine management scenarios designed to reduce nutrient and sediment delivery from the BCDC was the main for the model development. They found that the innovation of the Ben modeling system is to integrate otherwise separate modeling approaches.

Wohl and Rathburn (2003) depicted that the sediment entering the reservoir, creating sediment-depleted conditions at downstrem leads to channel adjustment in the form of bank erosion, bed erosion, substrate coarsening, and channel plan form change. They found the channel adjustment to increased sediment influx depends on the magnitude, frequency, duration and grain-size distribution of the sediment releases, and on the downstream channel characteristics. Mapping grain- size distribution, mapping shear stress and sediment transport capacity, mapping potential depositional zones, designing discharge and sediment release regime and developing plans to remove, treat, contain, or track contaminants, and to restrict establishment of exotic vegetation are the measures which have been suggested by them to mitigate sediment hazard at downstream.

Sternberg (2004) presented the study in the context of environment and societal needs. Dams act as geomorphic agents as well as water management structures. It is essential to anticipate a barrier's long-term environmental influence as well as to measure its long-term role in serving society. The analysis considers the varied magnitudes of dams and their respective functions to serve ever-larger populations. Dam size is a reflection of the changing dependence of society on specific water functions/services. As nature has its rhythm of change, the challenge is to fit human use into nature with minimal adverse environmental impacts. As with agriculture, dams have become part of the domesticated landscape.

Ecological problem caused on river ecosystem due to hydro power project has been pointed out by Maiolini et al. (2005). They have presented from the study conducted on Noce, a stream in the central-eastern Italian Alps, that the hydro-peaking affects the physical properties like temperature, conductivity, turbidity and oxygen etc. They also had shown the major hydro-peaking effects on the river biota like zoobenthic community.

Caruso (2006) presented that New Zealand's high country of the South Island, which has been severely impacted by hydroelectric power development. These braided rivers are highly dynamic, diverse, and globally important ecosystems and provide critical habitat to numerous native wading and shore bird species, including several threatened species such as the black stilt. They have carried out the Project River Recovery (PRR) after more than 10 years of implementation to provide information and transfer knowledge to other nations and restoration programs. The study found that PRR is an excellent example of an ecological restoration program focusing on conserving and restoring unique habitat for threatened native bird species, but that also includes several secondary objectives. Transfer of knowledge from PRR could benefit ecological restoration programs in other parts of the world, particularly riverine floodplain and braided river restoration. PRR could achieve even greater success with expanded goals, additional resources, and increased integration of science with management, especially broader consideration of hydrologic and geomorphologic effects and restoration opportunities.

Lajoie et al. (2007) have compared the monthly flow characteristics between natural rivers (76 stations) and reservoir-regulated rivers (25 stations) based on watershed size, using regression analysis on the monthly flows observed in Que ´bec. This study revealed that dams alter all monthly flow characteristics but the extent of these modifications is variable. Large watersheds are characterized by a greater inter-annual variability of the timing of maximum monthly discharges but a lower inter-annual variability of the timing of the minimum monthly flows than smaller basins. Concerning the monthly winter flows, large watersheds also exhibit an increase in the magnitude and a smaller variability in between years of discharges. Concerning the season, the hydrological changes were mainly observed in winter and spring. However, in both seasons, the extent of these hydrological changes varies from month to month. These results show that the dam-induced hydrological changes render the method of estimating minimum flow requirements in winter and spring inapplicable to reservoir dams in Que ´bec to protect Que ´bec fish habitats effectively. In winter, the method would underestimate the flows released downstream from the dams, while overestimating them in the spring. Moreover, the method cannot be applicable to all watersheds in certain.

Poff et.al (2007) presented that extensive construction of dams by humans has greatly dampened the seasonal and interannual streamflow variability of rivers, thereby altering natural dynamics in ecologically important flows on continental to global scales. The cumulative effects of modification to regional-scale environmental templates caused by dams is largely unexplored but of critical conservation importance. 186 long-term streamflow records on intermediate-sized rivers across the continental United States are used to show that dams have homogenized the flow regimes on third- through seventh-order Rivers in 16 historically distinctive hydrologic regions over the course of the 20th century. This regional homogenization occurs chiefly through modification of the magnitude and timing of ecologically critical high and low flows. For 317 undammed reference rivers, no evidence for homogenization was found, despite documented changes in regional precipitation over this period. With an estimated average density of one dam every 48 km of third- through seventh-order river channel in the United States, dams arguably have a continental scale effect of homogenizing regionally distinct environmental templates, thereby creating conditions that favor the spread of cosmopolitan, nonindigenous species at the expense of locally adapted native biota. They stated that quantitative analyses such as ours provide the basis for conservation and management actions aimed at restoring and maintaining native biodiversity and ecosystem function and resilience for regionally distinct ecosystems at continental to global scales.

Riggsbee et al. (2007) presented the impact on downstream of the dam due to dewatering or removal of the impounded water behind the dam. The quality of water due to dam removal affects a lot in the d/s up to few km from the dam axis. They have calculated the total suspended solids (TSS), dissolved organic carbon (DOC), and total dissolved nitrogen (TDN) loads for the different stages of dam removal at various points at upstream and downstream of the Lowell Mill Impoundment on the Little River, North Carolina. They found that the water released from the upstream was containing high amount of TSS and was retained up to 10 km below the dam. Dewatered Flood waves were sampled at different point up to 19.2 km at the downstream of the dam to characterize the routing of the TSS, DOC and TDN.

McCarthy et al (2008) presented on the management of ell stocks for the Shannon hydroelectricity. In order to negate a decline in juvenile recruitment resulting from the installation of hydroelectric facilities, management was focused on stocking lakes with elvers and fingerling eels. They have presented the long-term effects the hydroelectric facilities have had on the stock levels, there is also an annual effect on the migratory patterns of downstream migratory silver eels. They review previous work that had highlighted the importance of flow in determining the timing of the silver eels migrations, and assess the relationship between flow and migration in more detail through the use of hydroacoustic and telemetric studies. Current research on seaward migrating silver eel populations, suggests that spawner escapement rates can most effectively be increased by trapping migrating eels at fishing weirs located up-stream of the power station and transporting them towards the estuary.

2.3 Review of Previous Works on Reservoir Operation

2.3.1 Introduction

Reservoir operation policy plays a vital role in maximizing benefit and minimizing environmental losses due to the operation of reservoir. Therefore, development of an optimal operating policy for a reservoir is very much essential. Development of an optimal operating policy has been an active area of research for scientific community for the last four decades. Development and management of complex water resources system can be marked as a significant advancement made in the field of water resources engineering.

2.3.2 Linear Programming (LP) Models

a) Deterministic LP Model

Linear Programming (LP) is one of the most favored optimization techniques used for the reservoir operation. It has been proved from the past and recent research that LP is having many advantages like it is easy to understand and does not require any initial solution. If objective function and constrain are linear in nature, LP can be applied for reservoir operation problem. Good number of examples is available in literature where LP has been applied successfully for deriving optimal operating policy.

Dorfman (1962) demonstrated the LP technique in the reservoir operation and system planning problem. Parikh (1966) presented an approach of spatial decomposition by the application of linear dynamic decomposition programming of optimal long range operation of multipurpose reservoir system.

Branch comparison technique was first applied by Meier and Beighter (1967) to decompose the parallel reservoir system; in their approach they did not consider the temporal allocation over different seasons. Yeh (1985) reported that LP was applied to many reservoir operation problems.

Mujumdar and Teegavarapu (1998) introduced a deterministic LP model for short-term annual operation of an irrigation reservoir.

Unver and Mays (1990) developed a model for real-time flood control operation for a reservoir system and demonstrated that it is possible to link nonlinear optimization models with unsteady flow routing models to solve large-scale LP problems associated with flood control reservoir operation. In this method the nonlinear optimization is performed by using the generalized reduced gradient code GRG2.

Duranyildiz et al. (1999) presented a chance-constrained LP model, which takes the random nature of inflows into consideration to optimize the monthly operation of a real reservoir.

Wang et al. (2004) studied optimization of short-term hydropower generation and demonstrated that with the development of a direct search procedure, a reformulated problem with only linear constraints of outflow release and storage content can be solved.

b) Chance Constrain Model

Revelle et al. (1969) developed a chance constrained LP for reservoir optimization. In their study Linear Decision Rule (LDR) relates release to storage, inflow and decision parameter. In LDR, linear programming was imbedded as its optimization algorithm used to simulate the operation of the two hypothetical reservoirs. The results of the model showed an increase in the total benefits and the increase in benefit were higher when higher flow volumes were anticipated.

Bhaskar and Earl Whitlatch (1987) produced a model to derive optimal monthly relrase policy for Hoover reservoir locatede in Central Ohio using chance-constrained linear programming and dynamic programming-regression methodologies. Results indicated that dynamic programming policies produce lower average annual losses as compared to policies derived under the chance-constrained linear programming method while achieving at least as high reliability levels for the mean detention time and the corresponding safe yield target water supply release. In making that comparison, the reservoir release policies, although not identical, were assumed to be linear.

Duranyildiz et al. (1997) produced a chance-constrained LP model which considers the randomness of inflow in their study. That model was applied for the optimization of the monthly operation of a real water supply system. The results for different exceedance probabilities obtained by this model were compared with those obtained by a DP model.

2.3.3 Nonlinear Programming (NLP) Models

Hiew (1987) performed a comprehensive comparative evaluation of the successive linear programming (SLP), generalized reduced gradient (GRG), and a feasible form of successive quadratic programming (SQP) for hydropower systems of up to seven reservoirs, and concluded that the SLP method was by far the most efficient among the various nonlinear programming algorithms.

Grygier and Stedinger (1985) also concluded that SLP was the most efficient of the mathematical programming algorithms evaluated. In SLP, all nonlinear functions are linearized around an initial or nominal solution using the first two terms of the Taylor series expansion. Successive solutions are confined to specified trust regions or step bounds to avoid instabilities in convergence. Solution of the resulting linear programming problem then provides the basis for relinearization of the nonlinear functions, with the step bounds appropriately reduced as the process converges.

Tejada-Guibert et al. (1990) applied SQP to a five-reservoir portion of the Central Valley Project (CVP) of California using MINOS (Murtagh and Saunders 1987). The objective function includes nonlinear terms representing operating costs avoided and projects dependable hydropower capacity for each power plant. Constraints include nonlinear functions of energy production per unit release. A 3 - year optimization over monthly time steps resulted in a problem with 1,122 variables and 1,764 constraints. The authors note that computer execution times increase approximately to the square of the length of the operational period, which does not bode well for application of implicit stochastic optimization (ISO) over long time periods.

Dandy and Crawley (1992) developed operational policies for a system where water quality is considered highly important for the head works of the city Adelaide, Australia. In that study they considered the reservoir a completely mixed and LP model which was developed for the same system was modified and new policy was developed which minimize total system cost related to salt damage. They found that the modified policy was able to reduce the average salinity of the supplied water significantly.

A disadvantage of SLP is that ‘‘although intuitively appealing and popular because of the availability of efficient linear programming solvers, the method is not guaranteed to converge’’ Bazarra et al. (1993).

Arnold et al. (1994) applied SQP and MOM to the four-reservoir Zambezi River system in southern Africa over a 2 year period in monthly time steps. The model includes realistic nonlinear terms for hydropower production and evaporation calculations, resulting in a large-scale, dynamic optimization problem with nonlinear objective function and constraints. Results show that MOM converged more rapidly than SQP, but to a somewhat less accurate solution.

Peng and Buras (2000) also applied GRG (using MINOS) within an ISO scheme to the five major upstream lakes in the West Branch Penobscot River, Maine. Similar to the approach of Martin (1983), the GRG optimization is performed in monthly time steps over a moving 12 month forecast window.

Barros et al. (2003) developed a successive linear programming (SLP) model applied to the Brazilian hydropower system. The model is formulated in nonlinear programming (NLP). The NLP model is the most complex, but accurate model in the suite and particularly suited for setting up guidelines for real-time operations using inflow forecast with frequent updating. The performance of the NLP model was checked against the historical operational records, and the comparison yields indications of superior performance.Labadie (2004) in his recent review on multireservoir operation has enlisted some of the recent use of NLP in water resources system optimization.

2.3.4 Dynamic Programming (DP) Models

a) Dynamic Programming (DP)

Dynamic programming is a method of solving multi-stage problems in which sequential decision problems are divided into a sequence of separate, but interrelated, single-decision sub-problems. Dynamic Programming (DP) was first introduced by Bellman (1957), is an optimization technique to solve a multistage decision process. DP has been widely used in engineering and economic decision problem (Yakowitz, 1892; Yeh 1985).

WESTEX water quality simulation model in dynamic programming model to determine optimal policies for a multioutlet selective withdrawal structure was given by Fontane et al. (1981).

Hayes et al. (1998) integrated a water quality simulation model of upper Cumberland basin into an optimal control algorithm to evaluate water quality improvement opportunity through operational modification. The integrated water quality/quantity model maximizes hydro power revenue, subject to various flow and headwater operational restriction for satisfying multiple project purpose, as well as maintenance of water quality target.

Teixeira and Marino (2002) also developed a DP model to solve the problem of two reservoirs in parallel supplying water for irrigation districts. In the model, forecasted information including crop evapotranspiration, reservoir evaporation and inflows is updated, which allowed application of the model for real-time reservoir operation and generation of a more precise irrigation schedule.

b) Deterministic Dynamic Programming (DP) Models

Young (1967) was the first to apply the DP algorithm in reservoir operation. He studied a finite horizon single reservoir operation problem. After Young (1967) number of modified DP algorithms have been specifically developed to reduce the computational burden in DP when applied to multireservoir planning and operation problem.

Mays and Tung (2002) presented a method, in which large, complex problems can be solved by combining the solutions of the smaller problems (sub problems) to obtain the solution of the entire problem. It is well suited to deal with short-term operation (hourly or daily) when the hydrologic inputs and water demands are generally considered deterministic.

A brief review of past work has been reported on application of different type of deterministic DP in reservoir operation is presented below.

c) Discrete Dynamic Programming (Discrete DP)

Bellman and Deryfus (1962) were first to produce the concept of discrete dynamic programming (Discrete DP).

Hall et al. (1968) used the Discrete DP technique for optimizing operation of a multipurpose reservoir. The objective of their analysis was to determine for a given initial sate of the system, price schedule and sequence of inflow the set of decision regarding release of water from the reservoir that will maximize the total return from the operation subject to physical and other constrains.

Hall et al. (1969) modified their earlier method (Hall et al., 1968) by adding factors like firm water and on-peak energy constrains, energy pricing and flood control criterion etc.

Young (1969) first applied this Discrete DP approach to find the optimal operating policy of a single reservoir. He used release for current period as decision variable and initial storage for current period as state variable. Young (1967) first proposed a means to obtain rules from the results of the deterministic optimization model: he suggested performing least square regression against the preceding characteristics of the optimal operation such as pervious seasons' release, inflow and storage. In this way some of the stochastic nature of the optimal deterministic operation is captured in a general operation rule.

Roefs and Bodin (1970) made a critical analysis of reservoir operating rules using deterministic, implicit stochastic and explicit stochastic algorithm.

Mujumdar and Ramesh (1997) developed a short-term reservoir operation model for irrigation. The model consists of two components including operating policy model and crop water allocation model that were formulated using deterministic dynamic programming.

Archibald et al. (1999) presented a study based on computational comparison of nested Benders decomposition and dynamic programming (DP) for stochastic optimization problems arising from the optimization of hydroelectric generation from hydraulically linked reservoirs. They found that full DP results are within 1% of optimal and the DP decomposition results are within 3.2% of optimal.

Wurbs (1993) gave an idea of various modeling approaches for the evaluation of reservoir operation to help out the suitable model for particular application and to give better understanding about the usefulness of the so and so method in various types of decision-support system. He told that modeling and analysis approach for a particular application depends upon the characteristics of the application, the analysis capabilities provided by alternative models, and the background and preferences of the analysts.

d) Incremental DP (IDP) and Discrete Differential DP (DDDP)

IDP or DDDP provides a means to alleviate the curse of dimensionality associated with discrete DP. The IDP for reservoir operation studies was reported by Hall et al.(1969) and Trott and Yeh (1971) and systematize and referred to by Heidari et al.(1971) as discrete dynamic programming(DDDP). IDP uses incremental concept for the state variable, a concept first introduced by Larson (1968).The major difference between Larson's state incremental DP and IDP is the time interval used in the computation, which is variable in the former and fixed in the later.

Heidari et al. (1971) considered a prototypical four-reservoir problem, which was probably beyond the discrete dynamic programming because of cures of dimensionality. They proposed a computational technique called DDDP and gave a detail account of their numerical solution. The same hypothetical problem was also solved in the work of Larson (1968) to illustrate his computational procedure IDP.

Faults and Hancock (1972) applied the DDDP technique to five-reservoir problem of Central Valley Project (CVP) system in California, USA for an operation on daily basis. Later on Faults et al. (1976) applied the same technique in the same system for operation of nine reservoirs on monthly basis. In both the cases only the major storage were analyzed for maximization of power generation.

Nopmongcol and Askew (1976) analyzed the difference between IDP and DDDP concluded that DDDP is generalization of IDP.Tugeon (1982) demonstrated that IDP might converge to non-optimal solution if the same increment is used in every stage.

e) Folded Dynamic Programming (FDP)

The folded dynamic programming (FDP) is the recent technique of DP which is developed by Kumar and Baliyarsingh (2003) for application multireservoir system operation. The FDP algorithm is applied to a hypothetical four reservoir system problem of Larson (1968). The FDP is also applied in Hirakund reservoir to the develop optimal operating policy of a reservoir system for flood control by Kumar et al. (2010). In most of DP models like IDP, DDDP, IDPSA and DPSA, in which initial trial trajectory is necessary to start iteration. These authors have shown that FDP requires less number of iteration than other algorithms to arrive an optimal solution.

2.3.5 Stochastic Dynamic Programming (SDP) Models

Stochastic dynamic programming is an explicit stochastic optimization technique, which operates directly on the probabilistic description of random stream flow process (as well as other random variables) rather than deterministic hydrologic process (Labadie 2004). This means that optimization is performed without the presumption of perfect foreknowledge of future events. SDP formulations are traditionally adopted to deal with the stochastic nature of the inflows and it considers the inflow into the reservoir as Markov process (Howard 1960).

Moran (1954) produced SDP involved the derivation of the probability distribution of the storage state variable from either the pure analytical viewpoint, as in Kendall (1957), or through the derivation of transition probability matrices.

Butcher (1971) presented a study in which an optimal operating policy for a multipurpose reservoir was determined, where the optimal operating policy is stated in terms of the state of the reservoir indicated by the storage volume and the river flow in the preceding month and uses a stochastic dynamic programming approach.

Example of applications of explicit SDP models can be found in Stedinger et al. (1984).Yeh (1985) provides a state-of-the-art review of the applications of DP and SDP in reservoir optimization problems.

Klemes (1981, 1987) and Phatarfod (1989) reviewed the methodologies developed for analysis as a natural evolution of the stochastic theory.

Tai and Goulter (1987) introduced a heuristic iterative technique based upon stochastic dynamic programming and was applied for the analysis of the operation of a three reservoir 'Y' shaped hydroelectric system. That technique was initiated using historical inflow data for the downstream reservoir.

A SDP formulation was used by Pereira (1989) to derive optimal operating strategies of Brazil's hydrothermal system.

Kelman et al. (1990) developed a sampling SDP that captured the complex temporal and spatial structure of the stream flow process. They included the forecast for the current period as a state variable in determining optimal operating rules for reservoir operation.

Vedula and Mujumdar (1992) developed a model for optimal reservoir operation for irrigation using SDP. In their study, reservoir storage, inflow and soil moisture in the irrigated area were treated as state variables.

Tejada-Guibert et al. (1993) evaluated the effect on operation of using different state discretization and functional approximation within the SDP.

Vasiliadis and Karamouz (1994) presented a demand driven stochastic dynamic programming (DDSP). DDSP is an expanded version of BSDP developed by Karamouz and Vasiliadis (1992). In DDSP not only the prior transition probabilities of flow (historical and forecasted) are updated to posterior probabilities but also posterior and other probabilities are updated for a given specific month. DDSP includes the uncertain demands for each month as an additional state variable.

Nandalal and Bogardi (1995) presented a methodology to operate a reservoir for improving the quality of water supplied. This model can only provide the optimal outlet's release for a total release obtained from a SDP model.

Tejada-Guibert et al. (1995) produced reservoir operation policies derived based on SDP taking different hydrological state variables for the Shasta-Trinity system in northern California. The performance of the models was carried out for three different benefit functions, which placed penalties on corresponding storages for a benefit function with large water and firm power target and severe penalties on corresponding shortages, predicted performance was significantly overestimated then simulated performance while a benefit function stressing maximization gave nearly same output and the choice of the hydrologic state variable mattered very little.

Yang et al. (1995) combined an autoregressive model with DP to produce a SDP model that was investigated to provide steady-state operation rules taking into account the stochasticity of reservoir inflows.

Talukdar (1999) developed a SDP model for optimal operation of multipurpose Sardar Sarovar Reservoir of Narmada River, India.

Kim et al. (2007) presented state-of-the-art optimization techniques for enhancing reservoir operations which use sampling stochastic dynamic programming (SSDP) with ensemble stream flow prediction (ESP). These stochastic models are used to derive a monthly joint operating policy for Geum River multireservoir system in Korea.

2.3.6 Model Used as Combination of Two or More Methods

Bayazit and Duranyildiz (1987) presented a model for optimization of long-term operation of real world problem by dynamic programming. Due to limitation of computer timing it is necessary to use the iterative methods in the problems of multi reservoir system. It was found that state-incremental dynamic programming (SIDP) converges with reasonable rate if initial policies were suitably chosen for serial system. The authors proposed the new method, which combines successive approximation and SIDP. In this study Incremental sequential dynamic programming (ISDP) used to encounter the limitation of slow convergence rate by any other iterative methods for system of complex configurations. Applying in two case studies checked the usefulness of the developed model.

Karamou and Houck (1987) developed two dynamic programming models, one deterministic (DPR) and other stochastic (SDP) that may be used to generate reservoir operating rules and compared. These models were tested by generating reservoir operating rules on real-time reservoir operation simulation models which constructed for three hydrologically different sites. The model performance showed that the DPR generated rules are more effective in the operation of medium to very large reservoirs and the SDP generated rules are more effective for the operation of small reservoirs.

Paydays (1990) presented models for deciding the optimum system configuration in a river basin development problem considering long-term operational aspects of multiunit hydropower system, in Nepal. The objective of the model to minimize the monthly firm energy was achieved by applying the Incremental Dynamic Programming (IDP) technique, and then by the Stochastic Dynamic Programming (SDP) method which incorporates the stream flow stochasticity into the system. SDP maximizes the expected total annual energy generation subject to a prespecified monthly firm power output. Transitional Probabilities are derived from the available historical stream flow records.

Nanadlal and Bogardi (1995) introduced an optimization models developed for the derivation of operation policies for a reservoir when the quality considerations are important besides satisfying the quantity requirement. Reservoir operating policy was developed based on the Incremental Dynamic Programming Technique. The models were applied to a reservoir on the Shapur River in Southern Iran. The result found form these models were compatible that proved the potentiality of the model.

Ravikumar and Venugopal (1998) introduced an integrated real time operation method for a large-scale irrigation system in South India by simulation and SDP. The irrigation demand pattern was determined by the command area with historical data. The SDP was used to obtain an optimal release policy. This SDP model takes both demand and inflow as stochastic and followed first order Markov chain model. Finally another simulated model was used to study the degree of failure associated with adoption of the optimal operating policy for different reservoir storage at the start of the crop season.

Wen and Lee (1998) presented a neural-network based multiobjective optimization of water quality management for river basin planning and water quality control for the Tou-Chen River Basin in Taiwan. Their study overcomes the dependency of decision maker's (DM's) preference of traditional multiobjective decision making process by applying neural network algorithm to form a model for the solution of multiobjective problems of water quality in a river basin. In this study they have used back propagation algorithm of feed forward neural network to provide direct help to analyst involved in real applications.

Chandramouli and Raman (2001) developed a dynamic programming based neural network model for optimal multi reservoir operation Parambikulam Aliyar Project. Feed forward neural network is used in model development. The performance is compares with the regression-based approach and single-reservoir dynamic programming-neural network. The multireservoir model based on the dynamic programming –neural network found batter.

Chandramouli and Deka (2005) introduced a decision support model (DSM) based on artificial neural networks (ANN) for optimal operation of a reservoir in south India. The

DMS development was in combination of rule based expert system and ANN models. The training of the model was carried out using deterministic single reservoir optimization algorithm. The result of DMS based on ANN model outperforms the regression based approach.

2.3.7 Fuzzy Rule Based Modeling

Russell and Campbell (1996) presented fuzzy based reservoir operating rules by applying it on a single purpose hydroelectric project. They compare their results with the results obtained by deterministic dynamic programming. These concluded that though it is a promising approach, it suffers from the "curse of dimensionality". It can supplement the conventional optimization technique but cannot probably be a replacement.

Shrestha et al. (1996) proposed that the input to reservoir policies (e.g. initial storage, inflows and demand) as, well as output (e.g. historical release policies or results from implicit stochastic optimization) can be described by fuzzy relation. Authors reported excellent results by using fuzzy rule based system replicates actual historical operations of Ten killer Lake in Oklohoma.

Dubrovin et al. (2002) developed a fuzzy rule based control model for multi- purpose real time reservoir operation and found that it is batter to full fill the new multipurpose operational objectives determined by the experts.

Panigrahi1 and Mujumdar (2000) gave a methodology to construct a fuzzy rule based system for the operation of single purpose reservoir Malaprabha irrigation reservoir in Karnataka, India. The reservoir storage, inflow, and demands are used as premises and the release as the consequence. Simulated reservoir operation with a steady state policy provides the knowledge base necessary for the formulation of the Fuzzy rules. They have shown that the advantage of the fuzzy rule based reservoir operation is that complex optimization procedures are avoided, and linguistic statements such as ‘low inflow’ ‘poor rainfall’ etc., may be readily incorporated and easily operated by the operators. They have also concluded that fuzzy rule based model suffers from the curse of dimensionality, and therefore the applications of fuzzy logic to reservoir operation problems may remain limited to single reservoir systems.

Chaves et al. (2004) presented a fuzzy stochastic dynamic programming model (FSDP) for deriving optimal operating procedure. Markov chain technique is employed to handle stochastic characteristic of river flow. Artificial intelligence (AI) techniques are applied to simulate and analyzed water quality. In their study Organic matter and nutrient load are modeled as a function of river discharge through the help of fuzzy regression model based on fuzzy performance. It was found that the developed model provides an effective tool for reservoir operation.

Mousavi et al.(2004) introduced a model called fuzzy -state stochastic dynamic programming (FSDP), which takes into account both uncertainties due to random nature of hydrological variables and imprecision due to variable discretization. In order to show how effective the proposed method is, FSDP was applied to the Zayandeh–Rud river–reservoir system in Isfahan, in the central part of Iran, and was compared with a demand driven stochastic dynamic programming model and found better results than conventional techniques.

Mousavi et al. (2007) inferred that fuzzy regression (FR) is useful to derive operating rules for a long-term planning model, where imperfect and partial information is available where as adaptive network-based fuzzy inference system (ANFIS) is beneficial in medium-term implicit stochastic optimization, as it is capable of extracting important features of the system from the generated input-output set and represent those features as general operating rules. The methods are applied to a long-term planning problem as well as to a medium-term implicit stochastic optimization model.

2.3.8 Genetic Algorithm (GA) Model

During the last two decades, heuristic algorithms have been developed for solving reservoir optimization problems. These algorithms use a set of points simultaneously in searching for the global optimum.

Oliveira and Loucks (1997) proposed an approach to identify reservoir operating rules using genetic algorithms (GA) and argued that the approach overcomes some of the difficulties of many techniques based on more traditional mathematical programming models.

Chen (2003) successfully applied real coded GA in combination with a simulation model to optimize 10-day operating rule curves of a major reservoir system in Taiwan. The results showed that the method can be powerfully used to optimize the rule curves, not being limited by the type of the objective function and simulation model used.

A comparison between binary coded and real-coded GA was explored in optimizing the reservoir operating rule curves by Chang et al.(2005). The results showed that the new operating rule curves obtained from both methods are better than the current operation rule curves, and the real-coded GA is more efficient than the binary-coded GA.

Sarma and Ahmed (2005) introduced a GA model for finding optimal operating policy of a multipurpose reservoir for Pagladia Project at Assam in India. Which has been compared with the policy derived using SDP. They found that the GA based policy is better as compared to the conventional one. Sarma et al. (2006) applied the GA model to a nonlinear formulation of the optimal cropping pattern problem for Batadrava development block of Nagaon district of Assam, India. GA was found to be very efficient in deciding optimal cropping pattern considering real possibilities. They have also suggested the criterion for selection of suitable GA parameters.

Jothiprakash and Ganesan (2006) developed a GA based model to derive the optimal operational policy for a reservoir operation and it was applied to the Pechiparai reservoir in Tamil Nadu, India. The objective function was to minimize the annual sum of squared deviation from desired irrigation release and desired storage volume with the decision variables as reservoir release for irrigation and other demands (industrial and municipal demands). As the rule curves were derived through random search it is found that the releases were same as that of demand requirements. Hence based on case study it was concluded that GA model could perform better if applied in real world operation of the reservoir.

2.3.9 Ant Colony Algorithm

Zecchin et al. (2007) developed five ant colony algorithms and found to perform extremely competitively for water distribution systems WDS. They have conducted experiments to determine their performance on four WDS case studies, three of which have been considered widely in the literature and found that some among five developed models of ACO algorithms were very successful for WDS design, and two of the ACO algorithms outperform all other algorithms applied to these case studies in the literature.

2.4 Previous Works on Flow Forecasting and Synthetic Stream Flow Generation

2.4. 1 Traditional Methods

Conventional time series model such as Thomas Fiering model, autoregressive moving average (ARMA) model, auto regressive integrated moving average (ARIMA), autoregressive moving average with exogenous inputs (ARMAX) have n=been applied by many researchers in their studies, as they predict reasonably accurate result (Thomas and Fiering, 1962, Box and Jenkins, 1976).

Sen Z. (1978) developed a general mathematical model for the generation of synthetic monthly flows. The relevance of the model is its simultaneous preservation of lag-zero cross-correlations between successive months together with the first-order serial correlation of each month. It is shown that the conventional lag-one Markov model and the Thomas-Fiering model are special cases of the model presented. All of the necessary analytical expressions of the correlation structure of the model are derived. Finally, the fitting of the model to monthly flow data and the generation of synthetic sequences are discussed.

Yurekli and Kurunc (2004) presented the study which analyzed the monthly-minimum daily discharge data of each month from three gauge stations on Cekerek Stream for forecasting using stochastic approaches. The nonparametric test (Mann-Kendall) was used to identify the trend during study period. Two approaches of stochastic modeling, ARIMA and Thomas-Fiering models were used to simulate the monthly-minimum daily discharge data of each month. The error estimates (RMSE and MAE) of forecasts from both approaches were compared to identify the most suitable approach for reliable forecast. The two error estimates calculated for two approaches indicate that ARIMA model appear to be slightly better than

Thomas-Fiering. However, both approaches were identified as appropriate method for simulating the monthly-minimum daily discharge data of each month from three gauge stations on Cekerek Stream.

Kim and Valdes (2005) discussed that synthetic hydrologic time series can be used to quantify the uncertainty of a water resources system. Conventional parametric models, such as autoregressive moving average or Markovian models, assume that the variable under consideration is Gaussian. This assumption, however, is a shortcoming of parametric models and motivates the development of nonparametric approaches. Nonparametric models based on a kernel function have an innate low-order structure and are restricted to highly persistent variables. The study presented a seminonparametric (SNP) model that takes advantage of both parametric and nonparametric models to generate monthly precipitation and temperature in the Conchos River Basin in Mexico. By adopting a consistent and robust scheme from the Markovian model and a nonparametric mechanism to generate a distribution-free random component, the SNP model reliably reproduced sample properties such as mean, variance, correlation, and multimodality in the probability density function.

2.4.2 Artificial Neural Network (ANN) Models

New technologies and algorithms have come up as powerful tools for modeling several problems related to water resources engineering ANN is one of them. ANN has been used successfully to solve different kinds of hydrological problems (ASCE, 2000). The ANN approaches when applied to hydrologic time series modeling and forecasting have shown better performance than the classical techniques (Govindaraju and Rao, 2000).

Burian et al. (2001) stated that typically the generalization of prediction and accuracy of an application increases as the number of hidden neurons decreases; as the number of hidden neurons increases, there is a corresponding increase in the number of parameters describing the approximating functions. Hence the ANN network becomes more specific to the training data as the neurons in the hidden layer increases.

Karunanithi et al.(1994) demonstrated, how a neural network can be used as an adaptive model synthesizer as well as a predictor. Issues such as selecting appropriate neural network architecture and a correct training algorithm as well as presenting data to neural networks are addressed using a constructive algorithm called the cascade-correlation algorithm. The neural-network approach is applied to the flow prediction of the Huron River at the Dexter sampling station, near Ann Arbor, Mich. Empirical comparisons are performed between the predictive capability of the neural network models and the most commonly used analytic nonlinear power model in terms of accuracy and convenience of use. The results are quite encouraging. An analysis performed on the structure of the networks developed by the cascade-correlation algorithm shows that the neural networks are capable of adapting their complexity to match changes in the flow history and that the models developed by the neural-network approach are more complex than the power model.

Raman and Sunilkumar (1995) gave the artificial neural network (ANN) approach for the synthesis of reservoir inflow series which differs from the traditional approaches in synthetic hydrology in the sense that it belongs to a class of data-driven approaches as opposed to traditional model driven approaches. Most of the time series modeling procedures fall within the framework of multivariate autoregressive moving average (ARMA) models. They have investigates the use of artificial neural networks in the field of synthetic inflow generation. The performance of the neural network is compared with the statistical method of synthetic inflow generation. The neural network model provided a very good fit with the data, as the mean square errors were very low for the training samples. The results obtained using a neural network model compared well in the mean with those obtained using an autoregressive model. This indicates that a neural network offers a viable alternative for multivariate modeling of water resources time series.

Rivera et al. (2002) presented a model for multivariate streamflow generation is presented, based on a multilayer feedforward neural network. The structure of the model results from two components, the neural network (NN) deterministic component and a random component which is assumed to be normally distributed. It is from this second component that the model achieves the ability to incorporate effectively the uncertainty associated with hydrological processes, making it valuable as a practical tool for synthetic generation of streamflow series. The NN topology and the corresponding analytical explicit formulation of the model are described in detail. The model is calibrated with a series of monthly inflows to two reservoir sites located in the Tagus River basin (Spain), while validation is performed through estimation of a set of statistics that is relevant for water resources systems planning and management. Among others, drought and storage statistics are computed for both the synthetic and historical series. The performance of the NN-based model was compared to that of a standard autoregressive AR (2) model. Results show that NN represents a promising modelling alternative for simulation purposes, with interesting potential in the context of water resources systems management and optimizations.

Kumar et al. (2004) employed recurrent neural network (RNN) model in streamflows forecasting. Diamantopoulou et al. (2006) developed the three layer cascade correlation artificial neural network (CCANN) models for the prediction of monthly values of some water quality parameters in river Axios at a station near the Greek – FYROM, Strymon River, at a station near the Greek – Bulgarian borders for the study. The selected CCANN models gave very good results for both rivers and found promising to be applicable for the estimation of missing monthly values of water quality parameters in rivers.

Ahmed and Sarma (2007) presented an artificial neural network for generating synthetic stream flow series of the Pagladia River, Assam in India. They compared the performance of ANN model with two other models viz., autoregressive moving average (ARMA) model, Thomas-Fiering model and ANN model. The authors found that the ANN model is better in generating synthetic stream flow series for the Pagladia River.

Jain and Kumar (2007) proposed a new hybrid time series neural network model that is capable of exploiting the strengths of traditional time series approaches and artificial neural networks (ANNs). The proposed approach consists of an overall modelling framework, which is a combination of the conventional and ANN techniques. The proposed hybrid approach for time series forecasting is tested using the monthly streamflow data at Colorado River at Lees Ferry, USA. Specifically, results from four time series models of auto-regressive (AR) type and four ANN models are presented. The results obtained in their study suggest that the approach of combining the strengths of the conventional and ANN techniques provides a robust modelling framework capable of capturing the non-linear nature of the complex time series and thus producing more accurate forecasts.

Rivera et al. (2007) in their study discussed the influence of different hydrological input data on the management simulation of a water resources system (WRS). Three complete simulations were carried out using synthetic inflow series generated with several stochastic models: an autoregressive moving average (ARMA) model, the Lane condensed temporal disaggregation model, and a nonlinear model based on a multilayer perceptron artificial neural network (MLP-ANN) with a random component embedded. The validation of the stochastic models was performed using comparisons of relevant drought statistics from synthetic series with those from the historical records. Since the analyzed WRS includes five inflow sites, multivariate models were applied. The MLP- ANN model showed the best performance. The management simulations of the WRS were executed with the decision support system AQUATOOL under a probabilistic approach. This approach gives probabilities of demand failures of the WRS, which were used to evaluate the influence of the three applied stochastic models on the simulation results. Significant differences were found.

Solaimani and Darvari (2008) presented a comparative analysis of training methods and different data on rainfall-runoff prediction using ANN on monthly basis. Tow algorithms namely Conjugate Gradient (CG) and Levenberg-Marquardt (L-M) are compared for a watershed in Northern Iran. They concluded that L-M algorithm is more efficient than the CG algorithm.

Singh et al. (2010) discussed bout the capability of artificial neural network (ANN) models for predicting daily flows for Khosrow Shirin watershed located in the northwest part of Fars province in Iran. A Multi-Layer Perceptron (MLP) neural network was developed using five input vectors leading to five ANN models: MLP1, MLP2, MLP3, MLP4, and MLP5. They have attempted two activation functions logistic sigmoid and tangent sigmoid and Levenberg – Marquardt (LM) algorithm for ANN model development. They have concluded that the prediction of outflow is better with tangent sigmoid than logistic sigmoid activation function on 5-year data record selected randomly. The testing parameters selected for the model were R^2 and RMSE. It was found that antecedent precipitation and discharge with 1 day time lag as an input vector best predicted daily flows. Also, comparison of MLPs showed that an increase in input data was not always useful.

2.5 Conclusion

Review of literature has revealed that though several studies have been carried out to establish the fact that the reservoir operation causes adverse impact downstream, it appears that no study has been carried out so far to develop a procedure for estimating possible losses downstream due to reservoir operation.

Different conventional and advance soft computing tool have been applied so far for generating synthetic streamflow. ANN has been identified as a potential tool for generating synthetic streamflow. However, most of the previous studies were carried out for generating monthly streamflow series. Scope of using ANN for generating streamflow series of smaller time step, such as 10- daily, 8-daily and daily is yet to be investigated and there is a scope of research in this direction.

Though impact of diurnal variation of flow has been pointed out by different investigators, efforts to minimize such diurnal variation by operational strategy or other measure has not been attempted and this study focuses in minimizing diurnal variation by adopting different measures and by examining efficiency of these different measures through simulation study.

Scientific community has tried different optimization techniques for developing optimal operating policy. Different techniques have their own merit and limitation. While advance techniques like GA, ACO, has been found to be advantageous in some cases, well established traditional techniques like DP are also found to be reasonably good for practical applications.

Chapter 3

The River System and the Reservoir

3.1 Introduction

The description of the Lower Subansiri river system, proposed reservoir and its principal features have been presented in the chapter. The detail of the Lower Subansiri Hydro-Electric project has been obtained from the National Hydropower Corporation (NHPC) Ltd.

3.2 The River System

3.2.1 Basin Description

The river Subansiri originates in the south of the Po Rom peak (Mount Pororu) (5059 m high) in the Tibetan Himalaya. After flowing for 190 km through Tibet, it enters India. It continues its journey through the Himalaya of India for 200 km and enters into the plains of Assam through a gorge near Gerukamukh. The Subansiri is the largest tributary of the Brahmaputra. Its total length up to confluence of River Brahmaputra is 520 km and its drainage area up to its confluence of River Brahmaputra is 37, 000 sq. km. A study on spatiotemporal changes of this river since beginning of 20th century has shown that the river maintains an almost stable course in the hilly terrain, but has undergone significant changes in the alluvial plains of Assam during the last hundred years.

In the10 km reach from the foothills near Gerukamukh to Chauldhoaghat, the riverbed is composed of sand mixed with pebbles and boulders. Further downstream, it is mostly composed of sand. The average slope of the river bed from the foothills to 5km downstream of the dam is 0.000826, from 5km to 40km is 0.000354, and from 40km to the confluence of

Brahmaputra is 0.000165. The river banks from the foothills to Chauldhoaghat are composed mostly of sand, gravel and silt, beyond which they are composed almost exclusively of alluvial silt.

3.2.2 Climate and Rainfall

In the upper catchments, lying in the Subansiri District of Arunachal Pradesh, annual rainfall in the South is heavier than that in the Northern areas. During the monsoon period more than 70 percent of the rain occurs over the Southern half while in the Northern portions it is about 60 percent. Variability of rain fall for the monsoon and the year, as a whole, are relatively small. Average Annual Rainfall is around 1000cms (934.88cms during 2000, as per the record of Ziro, the district Headquarter of Subansiri district of Arunachal Pradesh.) Relative humidity is always high throughout the year except in the winter months, being slightly less humid. Generally, the area is moderately clouded in the period of March to May, heavily clouded to overcast in the monsoon season and clear or slightly clouded during the post monsoon season.

3.2.3 Stream Flow

Stream flow near the dam site varies significantly between monsoon and non-monsoon period. Average lean period flow is in the range of 500m^3/s and the monsoon period flow is in the range of 2500m^3/s. The average annual sediment yield at Chauldhoaghat is 94.83×10^3 mtonnes (WAPCOS 1993).

3.3 Lower Subansiri Reservoir

3.3.1 Location of Dam Site

The project located near North Lakhimpur town of Assam covers a part of district of lower Subansiri district of Arunanchal Pradesh and Dhemaji District of Assam. The location of the dam site on the river Subansiri is $27^0$33'15"N latitude and 94^0 15' 30"E longitudes.

3.3.2 Purpose of the Reservoir

The Lower Subansiri Hydro-Electric (LHSE) project is basically a power project, but it has a scope of flood moderation up to certain extent as the maximum reservoir level will be drown down during monsoon. In that sense the reservoir can be regarded as multipurpose. Primary objective of this project is to generate 2000MW of hydropower for a minimum of 4 hour peaking period.

a) Flood Control

The downstream area of the dam site is quite prone to flood. Therefore it is very important to keep enough storage space for the food accommodation, so that the water can be slowly released to downstream and hence flood hazards can be minimized up to reasonable extent. Though flood control is not a primary objective of this project, the project can still be used for the mitigation of flood situation by absorbing the

Table 3.1 Proposed Reservoir Elevations and Available Flood Storage Capacity

Period	Subansiri Lower (FRL = 205 m)		
	Reservoir Level (m)	Gross Capacity corresponding to conservation level (Mm^3)	Flood Cushion (Mm^3)
JUN-I	190.0	923.4	441.6
JUN-II	190.0	923.4	441.6
JUN-III	190.0	923.4	441.6
JUL-I	190.0	923.4	441.6
JUL-II	190.0	923.4	441.6
JUL-III	190.0	923.4	441.6
AUG-I	190.0	923.4	441.6
AUG-II	190.0	923.4	441.6
AUG-III	195.0	1060.7	304.3
SEP-I	195.0	1060.7	304.3
SEP-II	198.0	1143.1	221.9
SEP-III	205.0	1365.0	0.0
OCT-I	205.0	1365.0	0.0
OCT-II	205.0	1365.0	0.0
OCT-III	205.0	1365.0	0.0
November-I to May-III - Level varies between 205 m to 190 m			

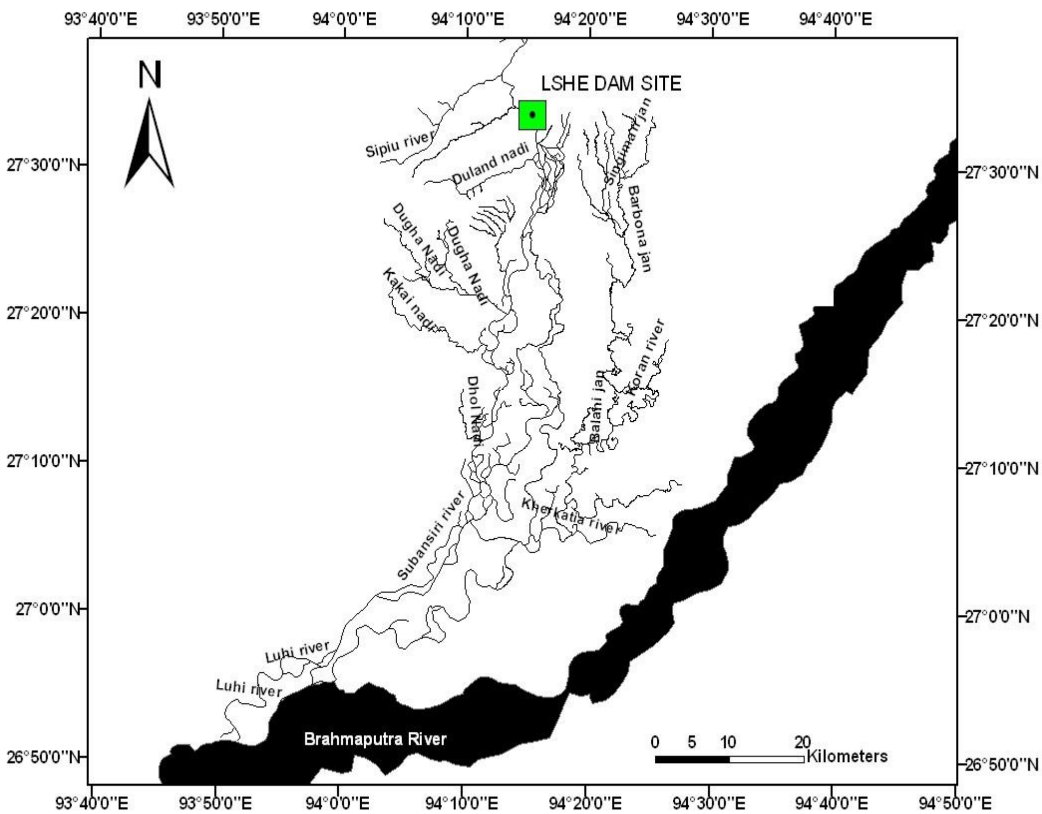

Fig 3.1 Location of dam site

flood temporarily and releasing later downstream. The proposed reservoir elevations and corresponding flood storage capacities at different time period is given in the table below (Table 3.1)

b) Hydropower Generation

This project proposes to have eight turbines and has an install capacity of 2000MW (250x8). Expected average annual power generation is 7421.55MU and it proposes to generate peaking power of 2000MW for a minimum of 4 hr in a day.

3.3.3 Principal Feature of the Lower Subansiri H.E.Project

This project is proposed for a full reservoir level (FRL) of EL 205.0m corresponding to a storage capacity of 1365.0Mm^3 and Maximum Water Level (MWL) of EL 208.25m with storage volume of 1470.0 Mm^3. The flood cushion of about 441.6 Mm^3 is provided for the period of high inflow like June, July and August months, which is the volume between EL 205.0 m and EL 190.0m. The maximum draw down level (MDDL) is 181.0m with storage volume of 720Mm^3. Height of the dam above river bed level is 116.0m and from the deepest foundation level is 133.0m.

Water from the dam will be diverted to the surge tank through side tunnel from where it will be delivered through eight penstocks having 9.5m diameter and with varying length of 106.70m, 106.88m, 106.64m, 106.46m, 106.34m, 105.82m, 105.86m and 106.004m for the target power generation of 2000MW (8 × 250). Maximum Tailrace water level is 112.0m and normal tailrace water is 108.96m whereas minimum tailrace water is 105.0m. The probable maximum tailrace water level is 122.5m.

a) Reservoir Capacity versus Elevation and Reservoir Area versus Reservoir Elevation Relationship

The Polynomial equation representing capacity versus elevation and area versus elevation has been found out by the method of curve fitting by using the data provided by NHPC for this Lower Subansiri project. The relations derived are given below:

<u>Capacity-Elevation Relationship</u>

For (S_t = 0 to 46)

$$Elevation(m) = \frac{128.5S_t + 1412}{S_t + 15.033} \qquad 3.1$$

For (S_t = 46 to 509)

$$Elevation(m) = 3.555\times 10^{-7} S_t^3 - 0.00045S_t^2 + 0.2561S_t + 9.40 \qquad 3.2$$

For (St =509 to1532)

$$Elevation(m) = 5.70 \times 10^{-9} S_t^{3} - 3.319 \times 10^{-5} S_t^{2} + 0.08358 S_t + 135.13.3 \qquad 3.4$$

where, S_t is reservoir capacity in Mm^3

Area-Capacity Relationship

$$Elevation(m) = -7E - 06A_t^{2} + 0.0543A_t + 99.726 \qquad 3.5$$

where, A_t is area of reservoir in Ha.

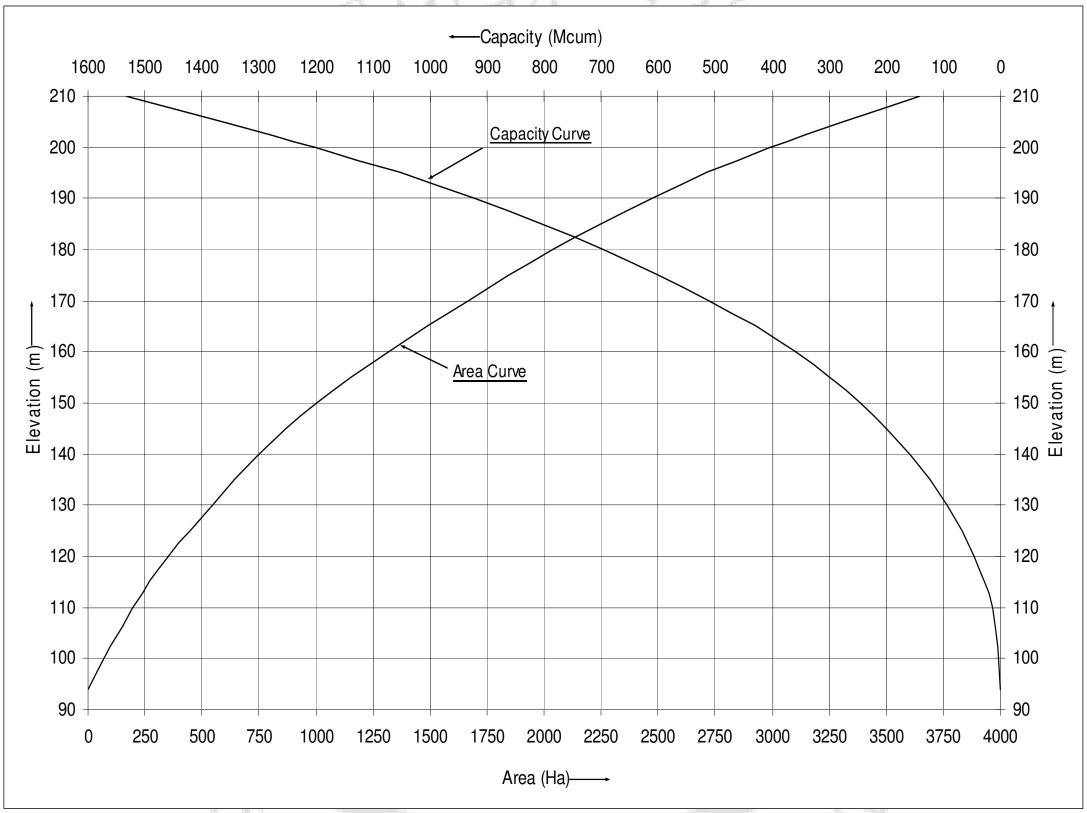

Fig 3.2 Capacity- area- elevation curves

3.4 Conclusion

Lower Subansiri reservoir situated on river Subansiri is proposed to serve two purposes namely power generation and flood control. The purpose of the power generation will be achieved with the generation of 7421.55 MU target power demand of the project. It envisages generating 2000MW power for a minimum of 4 hr peaking period. For the purpose of controlling flood the reservoir is proposed with flood control reserve storage of 441.6 Mm^3. Month wise ten daily flood accommodation strategy for wet period is presented in the table 3.1. As this project is a run-off-the–river project, it will not influence the seasonal flow. However, turbine operation will induce diurnal variation, which in turn will have some adverse impact downstream. To have a reservoir operation policy for obtaining net benefit considering downstream losses, a clear understanding of the downstream impact and losses is necessary. Next chapter, i.e. chapter 4 deals with the possible losses that may occur downstream.

Chapter 4

Downstream Impact

4.1 Introduction

Construction and operation of dam generally alters flow and sediment regime downstream. In case of hydropower dam, operated as peaking power plant, a large volume of water is seen during hours of power generation while meager amount of water downstream in the non operating hours of the day. Operation of hydropower project, therefore, affects the downstream to a great extent. However, it hardly gets proper attention as it is not visible immediately after the dam construction. In some cases, impacts of dam are seen quite far downstream from the dam site. Such dam-induced-flow scenario affects both quality and quantity of water and the downstream water scenario may become inadequate to meet the demand of inhabitants and river biota, particularly when these settlements and township depend only on the stream obstructed by the dam. Quantification of such impacts and their consequent losses are extremely difficult and subjective, but assessment of these losses in a logical way is essential to evaluate total net benefit from the project. This chapter aims to analyze various losses that may occur downstream due to operation of the dam. Issues related to hydropower dam have been given more emphasis considering focus of this study.

4.2 Disturbances Induced By Dam Operation

In general, operation of dam causes a cascade of effects on hydrology, river and floodplain morphology and riverine ecology with potential feedback loops (Naiman, 2001; Rood et al.2005). Jorde et al. (2008) proposed a hierarchy for considering operational impacts on floodplain ecosystems adapted from a frame-work originally proposed by Petts (1984).

The flowchart, shown in Fig 4.1 presents an idea of successive level of impacts and their hierarchal order.

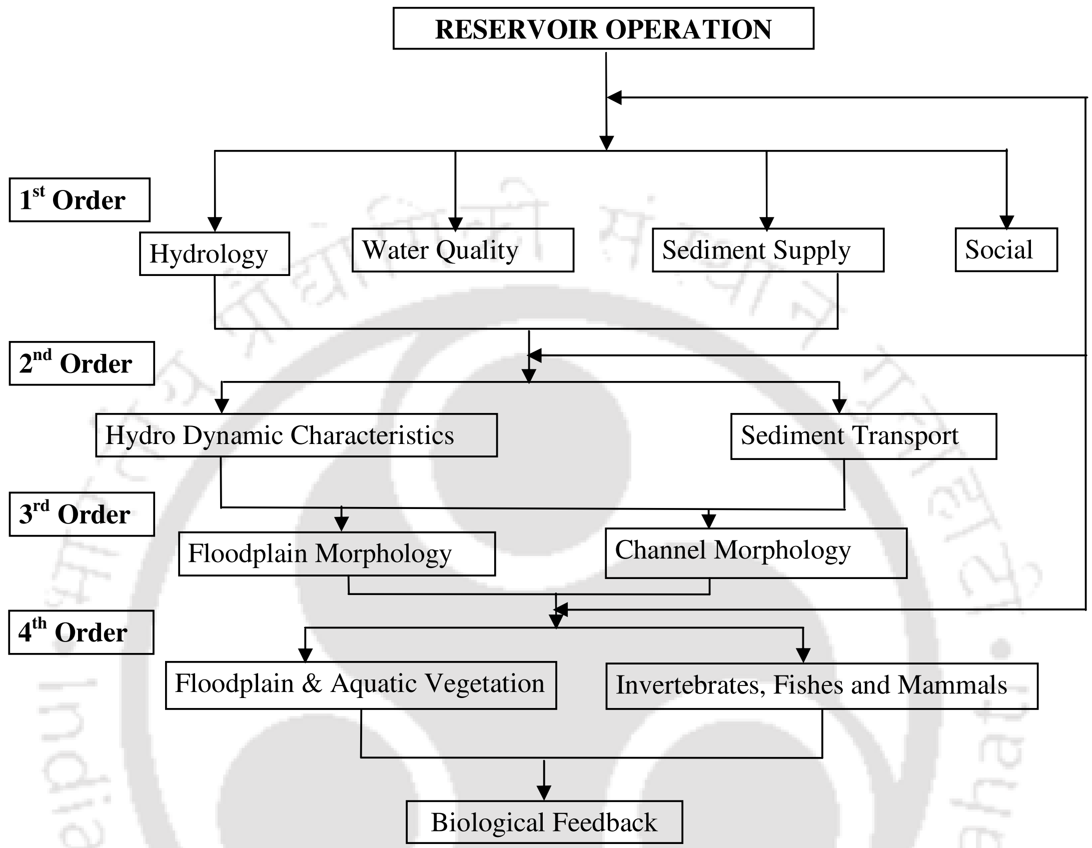

Fig 4.1 Successive level of impacts in hierarchal manner (Source: Petts, 1984)

Possible impacts as enumerated in the hierarchy model are discussed briefly in the following sections.

4.2.1 Hydrology

Generally run –of- the- river hydroelectric dams are constructed to raise the water level upstream in order to increase hydraulic head and to store water for a short duration and releasing it later to generate hydro power. Run- of- the- river hydroelectric project, designed for producing power in the peak hour with a provision of storing water during non-operating period, though does not change the seasonal hydrology, induces a diurnal variation of flow downstream. Putting in operation of such reservoir begets the hydrological changes in different ways downstream; change in diurnal variations of discharge due to the turbine operation is an example of such hydrological changes. The physical and ecological effects of such changes are generally seen several hundreds of kilometers downstream of hydroelectric dam. Above described flow scenario is result of flow regulation of a single dam. However hydrological regime change may also depend on the other dams in series upstream and downstream of the project in the same river basin.

4.2.2 Water Quality

Creation of reservoir and inundation of upstream may induce considerable change in the water quality. Biological, chemical and biochemical processes occurring upstream of the dam after its construction affects and changes the chemical composition of water to a great extent. Hence water released from dam does not possess the quality similar to that of the natural flow before dam construction. Within a few years of dam construction, biochemical changes occurring in the reservoir induce different kinds of poisonous gases and chemicals and these chemicals eventually enter in to the food chain of the fishes and birds downstream. Consumption of fishes grown in such environments by the human being and other species may increase health risk in human and other river biota downstream.

In case of hydroelectric project another issue of water pollution may arise because of flow variation downstream. With the decrease of flow rate downstream pollutants generated from both point and non point sources due to agriculture and industrial activities can increase the pollution level of the river reach downstream, as pollution concentration will increase even if pollutant generation remains the same. A study carried out in the LHSE project to explore the possibility of having inferior water quality downstream because of such dam operation is presented below.

Possible Impact on Water Quality Due To Operation of LSHE Project:

A 2000MW (250MW × 8) capacity LSHE project is currently under construction on the river Subansiri. This project has been designed as a run-of-the-river scheme primarily for meeting the power demand in the peak hours. Though variation in the total daily flow or seasonal flow may not be of much concern in a run-of-the-river scheme, the operation of turbine in this project is expected to induce significant diurnal variation of flow. This variation is more pronounced during the lean period, when the turbines are operated for 4 hours to meet peak demand. Mandatory environmental release during non-operational hours has been fixed as $6m^3/s$ as per the policy proposed by project management. An average inflow to the reservoir during lean period is in the order of $500m^3/s$. Thus water will be stored in the reservoir for about 20 hours to raise the head and to have sufficient water for producing 2000 MW of power during the 4 hours of turbine operation. During operational hours, the flow released downstream, will be in the order of 2500 m^3/s. Thus the diurnal flow variation will range between 6 m^3/s and 2500 m^3/s. This in turn will adversely affect the environment creating several problems at downstream of the dam. While realization of most of these impacts may take several years, some of these impacts may be experienced immediately after construction and operation of the dam. Some of such expected obvious impacts are highlighted below.

The dam is located just at upstream of the foot hills. Agriculture is practiced extensively in the alluvial plain downstream of the dam. Several villages and thickly populated townships are also situated within 20 km downstream of the dam. Chemicals fertilizers such as phosphate (PO_4), sulphate (SO_4) and nitrate (NO_3) used in these agricultural fields contaminate the river reach as non point source pollutants. The organic discharges from villages and urban centers located downstream also contribute to bacterial pollution. People residing in these townships and villages utilize the river water for various domestic purposes including drinking. A study conducted to assess the water quality status of this river reach has shown that, presently the water quality parameters such as phosphate, sulphate and nitrates are well within the permissible limit as per Indian Standard (IS: 10500). Contribution of these pollutants from upstream of the dam can be considered negligible because of its pristine nature. On the other hand, with the rise of population in the villages and the townships the contribution of non point sources pollutants is expected to increase. In the LSHE project, it is proposed to release only 6 m^3/s of flow as mandatory environmental release during the non-operational period. The peaking hour for the project being designed as minimum 4 hours, the minimum flow in the river can become as low as $6m^3/s$ for a maximum duration of 20 hours in a day during the lean period. It is worth mentioning that the natural average flow during the lean period (from December to March) is in the order of $500m^3/s$, minimum average being $341m^3/s$ in the month of January. Moreover, there is no major tributary of the Subansiri River within 23 km downstream from the dam. Thus, with reduction of flow rate due to reservoir operation, the pollutant concentrations are expected to increase and there is a high possibility that it exceeds water quality standards even if the pollutant load remains the same. A reach of about 10 km located downstream of the dam between 13km and 23km is considered for conduction a mass balance study of the pollutant load. The value of pollutants concentration observed at two locations in this river reach under MoEF sponsored project GIS based inventory for Rivers of North East India (Sarma et al., 2010) are used and average value is taken as representative value for this stretch. A simple steady state expression as given in equation 4.1 has been used for the mass balance study.

$$C_p = \frac{(q_l C_{pl} 2l + Q C_{po})}{(Q + q_l 2l)} \tag{4.1}$$

where, q_l is lateral unit discharge ($m^3/s/m$), C_{pl} is pollutant concentration (mg/l), Q is discharge of river (m^3/s) at upstream, l is length of river reach (m), C_{po} is pollutant concentration from upstream (mg/l); assumed as zero in this study. An estimated variation of pollutant concentration with change in downstream flow rate as obtained from the mass balance analysis is shown in the Fig 4.2. It is seen that the phosphate and sulphate concentrations may exceed the permissible limits due to flow reduction.

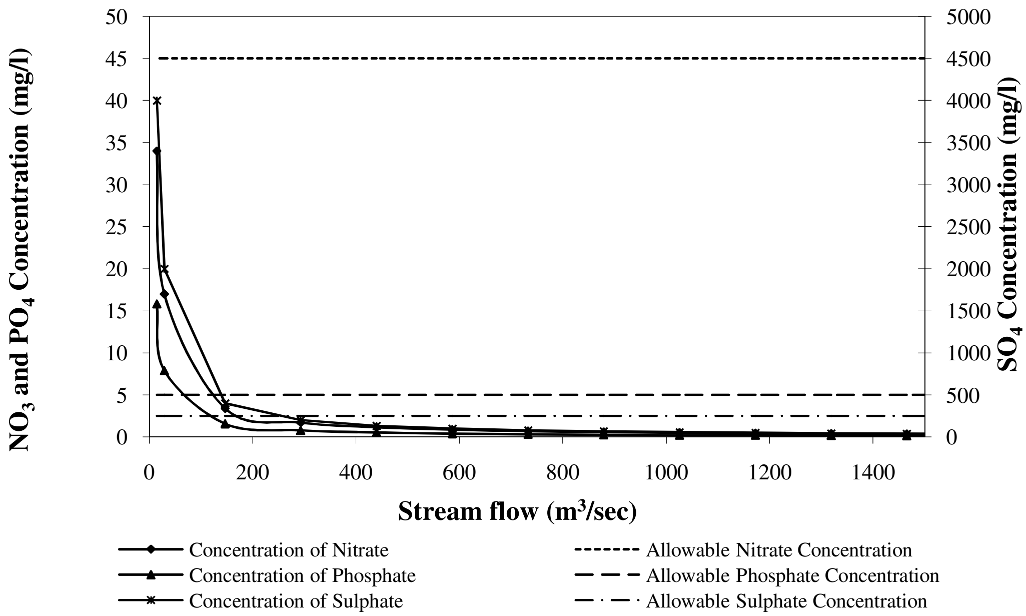

Fig 4.2 Estimated downstream pollutant concentrations and threshold levels as function of river flow.

4.2.3 Sediment Supply and Channel Morphology

Operation of reservoir can modify the sediment regime through alteration of deposition and erosion patterns downstream. Interruption and accumulation of sediment load upstream reduces the sediment supply downstream. Such sediment starved flow causes scouring and brings complex morphological changes downstream. The major changes of channel downstream can broadly be classified as bed degradation, channel bed narrowing, meandering and bank erosion. In any hydroelectric project which is operated for peaking power generation, high intensity of discharge for small duration during the operation of reservoir is most likely to induce high rate of erosion downstream. Frequent occurrence of these processes may accelerate degradation process in few kilometers immediate downstream while may cause increase in aggradations far way downstream. It was found that in large alluvial rivers, degradation processes are constrained to the first few or tens of kilometers downstream of the point of regulation, and a one to three meter depth of degradation typically occurs within a decade or two of regulation (Church, 1995). Such types of morphological changes are complex in nature and the response of the system will depend on several factors such as the characteristics of the alluvial deposit, number of tributaries joining at downstream, location of confluence points of these tributaries and their sediment load characteristics. Whatever may be the level of changes, establishing new equilibrium will be a time taking process and it depends on several factors including rate of vegetation growth downstream.

4.2.4 Flood Plain Morphology

Operation of reservoir will alter the extent and likelihood of the floodplain inundation and vegetation encroachment. Since floodplain formation is long and continuous process, morphological changes in the floodplain is significant due to changed flow regime downstream. Due to reduction in sediment supply and sediment laden flow, extent of floodplain may go on shrinking. Even, due to the effect of diurnal high intensity flows the topmost fertile layer of the old floodplain may get washed away making the floodplain less productive, even, sometimes old floodplains get completely vanished. However the formation of new floodplains is a long process. The floodplain soil downstream will remain infertile hence no longer exhibits a natural environment same as before the dam construction. These processes may significantly affect the complex and fragile ecosystem of floodplain downstream which is having a huge biological diversity.

4.2.5 Floodplain & Aquatic Vegetation

Dams designed to meet peaking power induces huge diurnal variation and variable water levels and flow regime as compared to storage kind of dam. Consequently, hydro electric dam can produce higher disturbances, on in-channel and riparian processes and related biota (Nilsson et al., 1997; Jansson et al., 2000). Hence, regulated discharges are often directly responsible for reduced habitat diversity and biodiversity in downstream reaches (Jansson, 2002). Although most responses to flow regulation are site-specific, general patterns of large-scale downstream effects are being observed worldwide and a synthesis of these is emerging (e.g., Dynesius and Nilsson, 1994; Nilsson et al., 1997; Rosenberg et al., 1997, 2000).

Intuitively, biotic communities should exhibit a dynamic response to opportunities presented by their environment; although the role of physical and biotic factors in structuring aquatic ecosystems is not always clear (Power et al., 1988; Rosenberg et al., 1997). To achieve a stable equilibrium becomes difficult in the conditions of rapidly changing physical characteristic that too in an unpredictable way. In general, damaged communities of colonizers, tolerant species and temporary residents established nearest to the dams are replaced by more natural communities downstream as conditions ameliorate and tributaries and groundwater exchanges return the river to a more natural regime (e.g., Ward and Stanford, 1989; Curry et al., 1994).

4.2.6 Invertebrate, Fishes, Birds and Mammals

The downstream biota experiences the newly disturbed regime; the effect of disturbance depends on the severity of change and distance from the dam. Disturbance to spawning resulting from the drawdown or rising of water levels, changes in seasonal temperature cycles, and blocked migration for fish are some major examples (Baxter and Glaude (1980) and Rosenberg et al. (1997)). Some species of the fish prefers to reside in particular area provided some criterion are fulfilled, viz. the depth and velocity of flow, type of river bed etc. Due to rapid changes in the immediate downstream of hydroelectric plants, the area may be deserted by such species. Such projects can pose serious effects on the existence of certain type of species those have their dependence on the river basin downstream. The changed food chain and altered ecosystem of the river may damage the species both living on and offshore. In many cases it has been seen that due to change in flow regime and physical and chemical characteristics of water, many species of fish and other river biota lost their habitats completely and permanently disappeared from the downstream.

4.3 Nature of Losses in Hydroelectric Projects

4.3.1 Productivity of Land and Agricultural Yield

The operations of hydroelectric projects induce obvious changes in the daily and hourly flow accompanied by depth, duration and extent of flow downstream. At the same time, the sediment coming from upstream generally gets interrupted behind the dam and water released from the dam is sediment deficit water, in other terms it is starved water having tendency to erode the downstream channel as well as the floodplain. All these processes ultimately reduce the fertility of land and lead to reduction in crop yield. Some of the study conducted on sample villages related to downstream impact of dam operation by Adams (1985) shows that significant fall i.e. 82 percent to 53 percent was observed on downstream agriculture in a village, while in other village the fall was about 60 percent to 40 per cent where as dry season cultivation fell from 100 percent to 27 percent. The changes in downstream flow may lead to change in ground water table and most of the time it was observed that it goes on decreasing. In such situation, excess burden of capital investment will increase on those farmers who depend on the ground water for the agriculture. Farmers dependent on the river flow get badly affected by the reduced flow condition.

4.3.2 Fishery

Due to operation of hydropower project there will be diurnal variations of flow which affect the downstream ecology up to several hundreds of kilometers. Fish production is main source of financial as well as nutritional aspects for many inhabitants downstream. Dam can affect fishery in many way like;

Natural flooding pattern: due to power scheduling huge discharge flowing the downstream during operational hours whereas meager amount of discharge flow downstream in non- operating hours. This significantly affects the fish production.

Degradation of river bed: Diurnal variation of flow will affect the physical stability of channel and induce degradation of channel downstream lead to loss of spawning ground for some kind of species.

Water Quality: Water released from turbine is comparatively cold that may be deoxygenate or may contain some harmful chemical, adversely affecting the fishes and other river biota.

4.3.3 Loss of Forest

During the construction of dam massive area of forest goes in submergence upstream, whereas construction of access road will reduce the forest cover and will increase the human interference.

The upstream population is forced to relocate; more land will be created and occupied downstream for the purpose of agriculture by the displaced. As a result deforestation will increase downstream which lead to destruction of habitat for many forest species putting them at risk. Furthermore, the downstream populations who depend on the forest as a primary source of food, building materials, medicine etc., their food security and livelihoods become vulnerable.

4.3.4 Loss of Riparian Zone

The operation of hydro power dams bring high fluctuations of flow in a day as the reservoir is to be operated to meet the peaking power demand. Riparian zone is the transition zone between land and channel stream. The magnitude of floods can hold different consequences for riparian ecosystems, as high-magnitude floods may create new geomorphic features and affect the entire landscape while smaller magnitude floods will influence ecosystems characteristics such as plant community structure or may only have impacts at the plant species level (Hughes 1997). The intensity and rate of the discharge downstream may affect the plant cover in riparian zone. Frequent diurnal variations caused in any hydro power projects may pose a sudden draw down condition on the river bank on an average repeatedly. Such situation may cause significant loss to herbaceous plants as those species are more likely to get damaged by the fluctuations of water levels as compared to woody trees. The processes of erosion and sedimentation will create temporary islands and sandbanks in the river bed and the growth of vegetation on such land forms will form a mosaic patches provide the habitats for colonization.

4.3.5 Reduction of Water for Domestic Use

Dams, particularly hydroelectric project, release large volume of water downstream for a few hours while turbine is in operation, whereas release becomes negligible during the non operating hours. Such a critical situation may cause the hydrological and hydraulic imbalance leading to dry river bed in conjunction of decline in water table in the vicinity. The human settlement or township residing downstream having their dependence on river for day to day work will drastically suffer and may result in shortage of water to fulfill their daily domestic demand.

4.3.6 Poor Nutrition and Hygienic Conditions

It has been found from the socio economic study that large number of rural population exist downstream of LSHE project. The habitants of this area are mainly dependent on various agriculture practices, fish production and forest downstream of dam for their livelihood. These means of livelihood greatly depends on the availability of water in stream and aquifers. Dam induced flow regime may be insufficient to meet agriculture, fishery or domestic need of the downstream population. These results in deficit crop yield, decline in fish production and reduction in forest cover ultimately affecting the food security and livelihood of the downstream dwellers. As these aspects have direct connection with health and nutrition it influences the life of inhabitants. The change in flow scenario seriously affects the recharging process of the aquifers downstream. As a result the water table keeps on going down and continuous depletion of ground water may lead to a situation that it may become difficult for the people to extract ground water from the aquifers in an economically viable way. On the other hand reduction in flow downstream may always pose shortage of domestic water. All these leads to poor nutrition and hygienic condition.

4.3.7 Loss of Employment /Livelihood and Uncertainty of Income, Poverty and Debt

Dam operation will change downstream flow scenario which ultimately causes different losses enumerated in preceding sections. These situations will be more significant, imposing uncertain income and migration in search of new employment for the rural downstream population whose livelihood is having direct or indirect connection with river. Reduction in flow downstream leads to decrease in many job opportunities for those who work in the agricultural farms, associated with fishing activity or having dependence on forest. Continuous happening of such phenomenon may push those farmers and fishermen towards poverty and debt.

4.3.8 Increase in Mental Stress

The families who are facing above mentioned situation will always be passing through mental stress. Women and children of those families will be most vulnerable because of migration and debt etc.

4.4 An Approach for Quantifying Some Significant Downstream Losses

Often, floodplain 'farmers' are also fish catchers, herders or dry land cultivators; sometimes all three (Adams 2000). This statement reflects the dependence of the downstream farmers on agricultural and fishery. The fact that the implementation of hydroelectric project adversely affects the agriculture and pisciculture downstream has been documented in a few past studies. Those studies were basically carried out on assessment of downstream impact for some existing project in operation since several years. However, little work has been found in the literature towards development of a methodology for quantification of downstream losses. Keeping in view the possible impact and nature of losses in hydroelectric projects, as a first step, two major losses i.e. agricultural and fishery which are generally very common to most of the projects are considered in this study. Therefore an effort has been made to develop a standard approach for quantification of losses that occurs in agriculture and fishery.

4.4.1 Assessment of Possible Agricultural Loss

Farmers residing downstream adopt distinct practices on the floodplain farming. Many a time downstream farmers do farming either on rising flood or receding flood. Floodplains are often made of alluvial soil which is most fertile soil and best for the farming purpose. Though there is high risk involved in floodplain farming, farmers apply their own judgment about the arrival and recession of the flood and net return have very high economic value. But construction of dam and operation of reservoir for producing hydroelectric power change the downstream flow scenario completely. Such changed downstream flow will adversely affect the downstream farming community. Many noted cases of the changed farming area and practice downstream of the dam are documented. Floodplain agriculture may be having considerable economic value although there are few formal studies. Barbier et al. (1998) calculated that the net benefits from agriculture in the Hadejia-Jama'are floodplain in Nigeria to be 239 Naira per ha per year (US$1 = 7.5 Naira). One case study on impact of dam construction on downstream agriculture is the Bakolori Dam completed in 1978 on the Sokoto River, (Adams 1985). In subsequent years it caused a significant reduction in peak flows, depth, duration and extent of inundation in the floodplain for 120 km downstream before the next major confluence with the River Rima (Adams 1985). River means something very important for the people residing nearby vicinity and having close association with river. When such rivers are controlled, a kind of uncertainty prevails among the downstream dwellers. In developing countries farmers living near river generally irrigate their field by pumping river water during lean period with the help of pump. Thus farmers will be suffering because of lowering of water level in the river. A schematic presentation of such irrigation setup is shown in Fig.4.3. A procedure for computing possible reduction in crop yield because of decrease in flow rate downstream in the river is discussed in detail in the following sections.

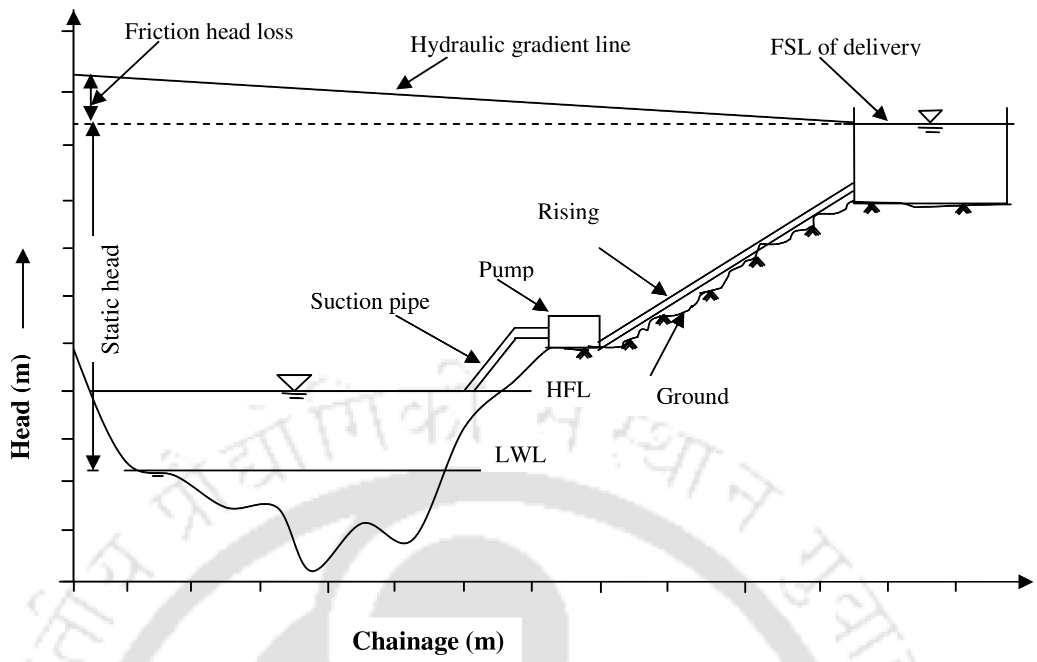

Fig.4.3 Schematic presentation of the pumping mechanism for irrigation

Agricultural losses that occur due to the diurnal variation in river water are discussed in this section. A procedure to work out such kind of loss is proposed. It has been already established that the farmers are drawing water from river in the lean season for the agriculture practices. It will be more important to address how the changing water level of the river downstream will affect their practice and additional operational as well as maintenance burden may be imposed on farmer.

Practical field losses such as loss due to reduced yield, loss due to extra pumping cost and losses due to requirement of extra accessories like pipe etc. are considered for computing the possible losses.

The flow rate downstream during day time, i.e., in the non operating hour will be very less during lean season, as most of the time hydropower plant will be operated in the night hours. However farmer usually utilizes the water of the river in the day time for the agricultural purpose. After construction of the dam, flow of the river will no longer remain same and it will pose a challenging situation to the downstream farmers. Because of reduced flow in the day time, farmers will not be able to have the required water for agriculture, which they used to get from the free flowing river. Such situation will lead to water stress in crop and this in turn would lead to decline in crop yields. Up to certain level of flow rate reduction, farmer will be able to get their required water by spending additional amount in pumping as the head difference will increase. However, beyond certain limit pumping will not be possible and crop will suffer grossly. Hence it will be worthy to do the analysis of the agricultural loss as river water level changes. The procedure for working out loss with respect to discharge is presented bellow.

1. The river cross section at a representative critical section located downstream is selected and its wetted area and perimeter corresponding to different water level is worked out.

2. Flow rate for different water level is then computed using Mannings formula and continuity equation. Basic objective of this exercise is to generate a discharge vs. loss relationship.

3. The static and total head is estimated with respect to reduced level of agricultural field and reduce level of river water.

4. Water requirement for agricultural purpose for the entire base period is estimated using duty-delta relationship.

5. It has been seen in many cases of dam, some of the farmers downstream are directly dependent on the river water for the agricultural activity. Up to certain level of water in the river the pumping is possible within affordable limit with the available pump set capacity. Beyond that level, further reduction in water level increase the time of pumping which will become quite expensive and will impose additional fuel cost as well as cost of the extra length of pipe. Hence analysis of availability of pump set and affordable duration of

pumping is necessary to be worked out. Using the capacity of pump set available, the delivery rate to the irrigation field is computed.

6. Based on the computed delivery rate, pumping duration required for irrigating the agricultural area in a day is estimated. If the total time of irrigation exceeds more than affordable pumping duration per day, then it will affect the crop yield as the crop will not receive the required amount of water. The water deficit is calculated when required duration is more than affordable pumping duration per day.

7. Total cost of fuel also increases if pumping duration increases.

8. Total cost of the pipe required to irrigate the field and additional cost of pipe for each change in the water level is worked out.

10. Theoretical and actual evapotranspiration is computed using Bleney-Cridel Method discussed in FAO (2000) the water balance equation as given below:

Blaney-Criddel Method

$$ET_o = P(0.46T_{mean} + 8) \qquad 4.2$$

ET_o = Reference crop evapotranspiration (mm/day) as an average for a period of 1 month

T_{mean} = mean daily temperature (°C)

P= mean daily percentage of annual daytime hours

$$ET_{crop} = ET_o \times K_c \qquad 4.3$$

where,

K_c = crop factor which depend on type of crop, growth stage of crop and climate

ET_{crop} (mm/day) =crop water need

Total volume of water required = ET_{crop} x Area of crop 4.4

$$\Delta W = IR + ER - ET_a - DP \qquad 4.5$$

where, ΔW =change in soil moisture (mm), *IR* = irrigation requirement (mm), *ER* = effective rainfall (mm), *DP* =deep percolation (mm), ET_a = actual evapotranspiration (mm/day).

11. Actual yield is estimated using the CROPWAT model developed by the FAO Land and Water Development Division (FAO 1992, Skalleriou-Makrantonaki and Vagenas 2006, Shah et al., 2000, Thakkar 1999). It is a simple water balance model that simulates crop water stress conditions and estimates yield reduction based on well-established methodologies for determining crop evapotranspiration (FAO 1998) and yield responses to water (FAO 1979). This model has been used to compute yield reduction percentage as a result of the decrease in evapotranspiration. The basic calculation procedure in this empirical model is:

$$1-\frac{Y_a}{Y_{\max}} = K_y\left(1-\frac{ET_a}{ET_m}\right) \qquad 4.6$$

Y_a = actual yield

Y_{max}= maximum yield

K_y = yield response factor which varies depending on crop growth stages

ET_a = actual crop evapotranspiration = ET_{crop}

ET_m= maximum crop evapotranspiration

12. The reduction in financial return is evaluated based on the market value of the crop produced.

13. The final model for the discharge vs. agricultural loss can be obtained by regressing the agricultural loss over discharge.

Application of Assessment of Possible Agricultural Loss in LSHE Project:

"We are closed to the river, we understand it through generation and living with it harmoniously but river is going to be controlled by dam and we will find it difficult to understand it's behavior"; these are the statements of an inhabitant residing downstream of LSHE project. As downstream community of LSHE project depends mostly on agriculture and fishery, these two aspects are more crucial and therefore considered for computation of losses because of which downstream community will suffer. Computation of agriculture loss is presented in this section.

The catchments area of LSHE project below the dam and up to the confluence of the river Brahmaputra is 2908 km^2. Out of that about 78 percent area is under agriculture (Kalita et al. 2010). Looking to the figures, area covered under agriculture practice is prominent in the lower catchments of LSHE project. As LSHE project is mainly constructed for hydropower, it will induce diurnal variation downstream when turbine will be operated for peaking power demand. This flow scenario will be completely different from the flow condition of a natural river. It becomes very clear from the Reservoir Simulation Model that during the hours of operation the rate of discharge will be more than $2500m^3/s$ where as non operating hour flow will be about $6m^3/s$, which is almost 500 times less than the operational hour flow. On the other hand the natural discharge of the river in lean period is the order of $500m^3/s$. It means construction of dam will reduce flow by 170 times in the lean period during non-operating hours as compared to normal flow. Hence it is very much important to do analysis of possible agricultural loss for different flow scenario downstream of the dam. It is observed that farmers close to river irrigate their field by pumping river water during lean period with the help of diesel pump. Thus agriculture activity will be suffering because of lowering of water level in the river. Given below are the few important points considered for the evaluation of agriculture loss.

1. Winter agriculture for a river reach of around 10 km, i.e. area located beyond 13 km (from where agricultural activity starts) of the dam and between 23 km (where other major tributaries join the main stream) from the dam site will be affected.

2. 10 percent of area located within 100m from the river bank is used for winter crop.

3. Thus approximately 10ha ($0.10 \times 100m \times 10{,}000m \times 10^{-4}$) of area will be affected.

General form for the same can be:

$$A = plb10^{-4} \tag{4.7}$$

where, A is area of under crop (ha.), p is percentage of area under crop (%), l is length of cropping area (m) along the river, b is width of cropping area (m)

4. Pump will be placed near the river and water will be pumped for a distance of on an average of about 1000m to reach the agricultural area located along the river. This distance is considered as 1000m as the flow during lean period will not be very near to the bank and the actual plot may be located at far distance from the pumping point.

Thus a total plot of 10ha located within the reach is considered for loss assessment. A section located at a distance of 15 km downstream from dam site has been considered as a representative section for developing stage discharge relation. Analysis is performed on the crops that are grown in the lean period i.e. October to April.

It was found from the socio-economic study of the area that inhabitants living downstream of LSHE project belongs to poor economic class. Hence they cannot afford to own the pumping equipments, rather they higher the pumping sets as per their requirement. As many small land holder need to share the pump set, it was observed that generally pumping set is not available for more than three hours in a day with a farmer for irrigating their land. Based on the present status regarding availability of pump set, for the purpose of analysis, it is assumed that a 6HP diesel pump set will be available to the farmer for a maximum of 3 hours in a day. Using the 6HP pump set the delivery rate to the irrigation field is computed. Using the procedure cited above, the complete assessment of the loss is carried out.

The table showing computed loss in terms of Indian Rupee against different discharges is presented in Table 4.1. Fig 4.4 shows the plot between discharge and agricultural loss.

Table 4.1 Discharge vs. total agricultural loss

Water level (m)	Discharge (m^3/s)	Total fuel cost (₹)	Extra cost of pipe (₹)	Agricultural Loss (₹)
97.44	1878.116	245.2874	75	9620.234
96.16	939.0077	286.8175	128	17679.71
95.75	698.0881	300.1202	169	19792.04
95.50	592.0099	308.2315	194	20991.12
95.25	461.8878	316.3429	219	22129.13
95.00	345.9472	324.4542	244	23210.65
94.75	266.1315	332.5656	269	24239.8
94.50	207.0193	340.6769	294	25220.33
94.25	147.1358	348.7883	319	26155.63
94.00	119.6649	356.8997	344	27048.79
93.75	89.7753	365.011	369	27902.61
93.50	52.7609	373.1224	394	28719.67
93.00	6.0000	399.3451	444	29885.35

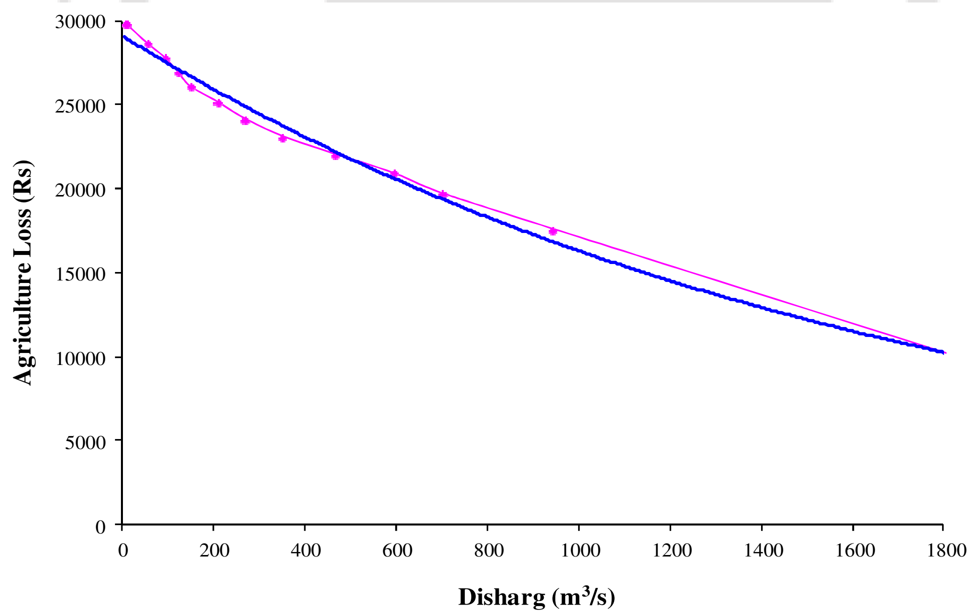

Fig. 4.4 Discharge Vs Agriculture Loss

The final model for the discharge vs. financial loss is presented in equation given below.

$$L_{fat} = 28987 e^{-0.0006 Q_{nt}} \qquad 4.8$$

where, L_{fat} = Loss in agriculture (Rs.) at any time t and Q_{nt} = discharge (m^3/s) in non operating hour after the dam construction.

4.4.2 Assessment of Possible Loss from Fish Production

Fishing is one of the common activities in the majority cases of the downstream of the dam throughout the world, but operation of reservoir and dam induced flow regime is a question mark for the aquatic culture to survive, upon which fish habitation is dependent particularly when the dam is hydropower project. The river not only provides habitat and food for the fishes but also regulate their life cycle through flood water. Fishing activity is continuous throughout the year except their breeding season. Fishing provides food and income or cash to the people. The dependence of local people on the river was found from the socio-economic studies conducted by an expert group constituted for downstream impact study (Kalita et al. 2010). The assessment of fish production depends on various factors; mainly, the type of fishes, their favorable aquatic culture, the change of flow regime, high and low flow, quality of water coming to the downstream from the reservoir, velocity of flow, slope of river bed, sediment characteristic of flow and many more. Hence the detail study is required to understand their behavior and response towards changed flow regime. As diurnal variations are quite significant in the hydro electric projects their response to the altered flow regime may be different. In absence of detail information about the fish loss characteristic with the flow, a linear variation has been assumed. To address this aspect a weighting factor w_t is considered, value of which will vary depending on the fish verity. Again impact of percentage deviation of flow on fish production will be different at different season. Thus w_t will also depend on the time. Thus loss of fish production can be computed by the equation give below.

$$L_{fpt} = w_t \times \left(\frac{Q_t - Q_{nt}}{Q_t} \right) \times L_{fft} \times R_f \qquad 4.9$$

where, L_{fpt} = loss in fish production (Rs.) at any time t, Q_{nt} = discharge (m^3/s) in non operating hour after the dam construction, L_{fft} = ten daily fish production (kg) at any time t, R_f = selling rate of fish per kg (Rs), Q_t = natural discharge (m^3/s) before dam construction and w_t = weightage factor that depends on fish variety and season.

Application of Assessment of Possible Fish Production Loss in LSHE Project:

Next to the cultivation, the fishing is the dominant activity downstream of the LSHE project. Almost 55 different kinds of fishes are found in the downstream of Subansiri. Diverse habitats like riparian wet lands, meandering cut off (static water body), oxbow etc. provided by the Subansiri are the rich habitats of many native fishes (Hazarika et al., 2008). Fishing activity is continuous throughout the year except their breeding season (March - June). Peak fishing season is during October - January. Fishing provides food and income or cash to the people. On an average about 45 percent inhabitant downstream LSHE project depends directly on river where as almost 26 percent is on fishing activity for their livelihood and needs of day to day life. On the other hand the area of the Dhemaji and the Lakhimpur district of Assam, which are among the major fish producing districts of Assam encompasses more than 90 percent of the Lower Subansiri basin of downstream of the dam. If we observe the figures of fish production in these two districts for the year of 2007-2008 (Statistical Handbook Assam, 2008) it is seen that fish produced in these two districts are: 10672 Tones from Lakhimpur while 3364 Tones from Dhemaji, which is almost 8 percent of the total fish production of Assam state. The regulation of river and changed flow scenario will directly affect the fishing activity of these districts.

Considering the aspects of downstream fishing, if, a minimum of $250m^3/s$ discharge is provided to the downstream, the fishing activity more or less can be maintained. The reason of the providing 250m^3/s is that the lean period flow of the river without dam is about 500m^3/s while some tributaries downstream will also be adding some amount of discharge to river Subansiri, hence releasing 250m^3/s will be able to restore the natural equilibrium of the river. A study on fish production was conducted in the downstream of Subansiri basin by dividing the same in four sector starting from the downstream of the dam up to confluence of the river Brahmaputra. From this survey monthly fish production in different sectors were assessed as given in Table-4.2. As it is considered that 250m^3/s discharge is required for normal breeding and growth of fish downstream, the discharge available downstream on ten daily basis will be verified and if the discharge is greater than the required discharge in breeding season the loss will be zero else it will be computed using following expression. As various spices may exist in the downstream of the LSHE project and their response to the altered flow regime may be different and therefore it requires a detail study to understand the behavior of those species toward changed flow scenario. To address this aspect the loss from fish production is computed as product of deviations of discharge in non-operating hour and ten daily fish production with weightage w_t.

Table 4.2 Month wise fish production in the lower catchments of LSHE project

Months	Sector wise fish production (Tonnes)				Month wise total fish production (Tonnes)	Ten daily total fish production (Tonnes)
	Sector-I	Sector-II	Sector-III	Sector-IV		
January	0.8	4.1	7.2	8.8	20.97	6.99
February	75	4.6	5.4	7.2	17.95	5.98
March	8	4.7	5.5	7.3	18.3	6.10
April	88	5.1	5.7	7.6	19.28	6.43
July	5	9.7	15.3	15.1	41.6	13.87
August	6	10.2	16.1	16.4	44.3	14.77
September	4	10.1	15.7	17.4	44.6	14.87
October	4	11	16.9	16.3	45.6	15.20
November	2	7.7	13.4	14.4	36.7	12.23
December	1	4.9	10.4	10.2	26.5	8.83

$$L_{fpt} = w_t \times \left(\frac{250 - Q_{nt}}{250} \right) \times L_{fft} \times R_f \qquad 4.10$$

where, L_{fpt} = loss in fish production (Rs.) at any time t, Q_{nt} = discharge (m^3/s), L_{fft} = ten daily fish production (kg) *at any time t* form Table-4.2, R_f = selling rate of fish per kg (Rs)) i.e. 50 Rs per kg and w_t = weightage given to the fish production.

4.5 Conclusion

The downstream impact caused due to reservoir operation has been discussed in general and specific for the hydropower project. As a consequence of impacts, losses occurring downstream are also discussed. In most of the dam projects it is seen that the community residing downstream of the dam, generally depends on the agriculture and fishing activity for their livelihood and food security. Hence, if the river is obstructed by the construction of dam these two important aspects of the human dependence may be affected badly. Therefore a standard approach for the loss assessment taking into account the two most significant losses i.e. loss of agriculture and loss of fish production has been developed in the present study. The applicability of the developed approach has been verified through its application for loss estimation downstream in LSHE project. The present study depicts, the exponential fall in monetary return from agriculture if discharge decreases downstream. The response of fishes towards changed flow scenario downstream may be different and it may vary from species to species, hence a linear variation has been assumed. The weightage factor w_t is introduced for the loss quantifications to overcome the uncertainty of their behavior towards altered flow regime.

Chapter 5

Problem Formulation

5.1 Introduction

This chapter deals with the problem formulation for optimization of the reservoir operation for the LSHE project. The problem formulation is carried out on the basis of ten daily data considering some physical constraints and keeping in mind the purpose to be served by the reservoir. Here formulation of optimization problem means the derivation of set of mathematical expression of the objective functions and constrains for the dam project.

5.2 Physical Feature of the Reservoir and Distributory System

Flood control and hydropower generation are two primary objectives which is served by the LSHE project, in addition some secondary objectives like downstream water quality, channel capacity and flood damage etc. are also expected to mitigate. The reservoir is proposed to operate from a storage volume of 720 Mm^3 (MDDL) to 1365 Mm^3 (FRL) in lean season and 720 Mm^3 (MDDL) to 923.4 Mm^3 (MRL) in wet season. Thus the conservative storage 645 Mm^3 is in lean period and 203.4 Mm^3 in wet period. To meet the objective of flood control reservoir is planned with the flood control reserve storage of 441.6 Mm^3, that is the storage space between RL 190.00m (MRL) to RL 205.00m (FRL). The reservoir also needs to meet peaking hour power demand of four hours.

5.3 Objective Functions and Constraints

5.3.1 Objective Functions

The purpose of optimization is to choose the best of many acceptable designs or policies available. Thus a criterion has to be chosen for comparing the different acceptable designs or policies and for selecting the best one. The criterion with respect to which a design or policy is optimized, when expressed as a function of the design variable, is known as the objective function (Rao, 1996). The choice of the objective function is governed by the nature of the problem.

Considering the target power demand maximization of the power profit is taken as the objective function in this study with release as decision variable. This project is planned for the peaking hour power demands; therefore maximization of the power benefit is more advantageous form the management point of view. However considering the fact that the reservoir induced diurnal variations will have some adverse impact on the downstream and will cause some losses, the objective function in this study has been designed to have maximum net benefit, i.e. benefit obtained after deducting losses that occurs downstream from the power benefit. The major losses that affect the livelihood of the downstream community directly are considered for assessing the losses. The losses taken into account are; loss of agriculture and loss of fish production due to diurnal variations. Details of these losses are given in chapter 4. Mathematical expression of the objective function is given below:

$$Maximize\ f = \sum_{t=1}^{T} \left(P_{bit} - (L_{fat} + L_{fpt}) \right) \qquad 5.1$$

where,

P_{bit} = profit from power production during time period *t;*

L_{fat} =loss of agriculture at downstream due to water scarcity at time period *t*;

L_{fpt}= loss of fish production at downstream due to water scarcity at time period *t*;

T = 3600; 36 stages per year for 100 years.

The expanded form of equation 5.1 is written in equations 5.2 to 5.6

Maximize

$$f = \sum_{t=1}^{3600} \left[\left(\frac{1}{2} \eta g Q_{dt} (H_n + H_{nn}) R_p H_r \right) - \left(\left(28987^{-0.0006 Q_{nt}} \right) + \left(w_t \times \left(\frac{250 - Q_{nt}}{250} \right) \times L_{fft} \times R_f \right) \right) \right] \quad 5.2$$

$$Q_{dt} = \frac{R_t \times 10^6}{H_r \times 3600} \quad 5.3$$

$$Q_{nt} = \frac{(S_t + I_t - R_t - E_t - K_{El}) \times 10^6}{(240 - H_r) \times 3600} \quad 5.4$$

$$H_n = El_t - El_{tail} - h_f \quad 5.5$$

$$H_{nn} = El_{nt} - El_{tail} - h_f \quad 5.6$$

t = index of time period (10 days);

H_r= Duration of turbine operation (hour);

η = the combined efficiency of turbine and generator in percent in %;

g = gravitational acceleration (9.81) m/s^2;

Q_{dt} = discharge passing through turbines m^3/s for time t;

Q_{nt} =discharge in non-operating hours m^3/s for time t;

L_{fft} = fish production (kg) for time t;

w_t= *weightage* given to fish production;

R_f = cost of fish per kg (Rs);

H_n= Net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at beginning of time t (m);

H_{nn}= Net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at end of time t (m);

S_t = reservoir storage (a state variable) at the beginning of time period t (Mm^3);

I_t = inflow at time t (Mm^3);

E_t = evaporation at time t (Mm^3);

R_t = release at time t (Mm^3);

K_{El} = Storage capacity of reservoir at time t (Mm^3);

φt = discrete set of characteristic storage volumes considered at the beginning of time period t;

n = total number of time periods remaining including the current period before;

El_t =elevation of reservoir at the beginning of time t (m);

El_{nt} =elevation of reservoir at the end of time t (m);

El_{tail} =elevation of normal tail race water (m);

h_f = head loss due to friction (m) corresponding to El_t and El_n;

R_p= cost of power (Rs.) per unit (kWh).

5.3.2 Constraints

a) Continuity Constraint

$$S_{t+1} = S_t + I_t - R_t - E_t - R_m \qquad 5.7$$

where,

S_{t+1} = storage in Mm^3 at the end of the time period t or beginning of time period $t+1$;

R_m = minimum downstream release = $6 \times 10 \times 24 \times 3600/10^6$ which the project proposes to release primarily to meet the water requirement of river reach between dam and the tail race confluence.

b) Reservoir Storage Constraint

Reservoir storage cannot be lowered below the dead storage volume of 720 Mm^3. The maximum storage of the reservoir at beginning or the end of ten days cannot be more than storage capacity of the reservoir which is given in table no 3.1 in chapter 3 in order to accommodate for coming flood in the reservoir. But in any case it should not be greater than full reservoir level (FRL) volume of the 1365 Mm^3.

Thus the reservoir storage constraint is given as;

$$S_d < S_{t+1} < S_{max} \quad ` \qquad 5.8$$

where,

S_d = Storage capacity of the reservoir at MDDL = dead storage volume = 720 Mm^3;

S_{max} = storage capacity of reservoir at FRL =1365 Mm^3.

c) Release constraint

Release from the reservoir should be such that at the end of time t it the reservoir storage level does not go above FRL and does not go below MDDL

$$R_{t\min} < R_t < R_{tmax} \qquad 5.9$$

where,

$$R_{t\min} = \max[0, (S_t + I_t - E_t - K_{El} - R_m)] \qquad 5.10$$

$$R_{t\max} = S_t + I_t - E_t - S_d - R_m \qquad 5.11$$

In above equations

R_{tmin} = minimum release in time t based on reservoir storage constraint;

R_{tmax} = maximum release in time t;

K_{El} = reservoir storage capacity considering flood cushioning at time t;

C_{Kd} = downstream channel capacity;

d) Downstream Environmental Constraint

In the lean period, inflow to the reservoir reduces and LSHE project being run-off-the-river scheme, the release made from the reservoir in lean period also gets reduced. In such situation it becomes very important to maintain the minimum release to meet the downstream water quality standards which is essential for the survival of the aquatic life and human being residing at the downstream of the river. Thus another release constraint is.

$$R_t \geq R_{tdm} \qquad 5.12$$

where, R_{tdm} is the minimum mandatory flow that policy maker may decide to provide at downstream to maintain near natural flow. 250 m^3/s is considered for the present study to conduct the case study.

5.4 Conclusion

The optimization problem for the development of the ten daily operating policies for the LSHE project has been formulated in this chapter. Maximization of net benefit, i.e. the monetary benefit obtained from power after deducting the monetary loss in agriculture and fishery downstream, has been consider as the objective function. To meet other environment need a provision of mandatory release is also being kept in the problem formulation. The flood control has been set as constraint of the optimization problem by keeping the flood cushion by maintaining the reservoir level in different period as per the proposed strategy. Application of this model to LSHE project is given in detail in the chapter 8.

Chapter 6

Synthetic Streamflow Generation

6.1 Introduction

Proper planning, efficient management and optimal operation of the water resources system is an utmost need of the recent time. Earlier, water resources planners used to handle planning and management with the only available historical hydrological records. Those approaches have a limitation in their planning because of insufficiency of long series of data. Development of the best policy for the reservoir operation requires a long time series of streamflow. The Lower Subansiri Hydro-Electric (LSHE) project considered in the present study has limited historical streamflow data. As such, this data set is not sufficient to develop a generalized optimal operating policy. The developed operating policy needs to be evaluated through simulation model of the reservoir using streamflow series which were not used to develop the operating model. Hence a longer data series for the LSHE project has been generated synthetically with respect to different time step viz. monthly, ten daily, eight daily, six daily, five daily and daily. In this chapter 100 years of synthetic streamflow of LSHE project for different time step have been generated using three methods, Thomas-Fiering model, Artificial Neural Network (ANN) model and Hybrid model. MATLAB programming has been used to develop all these three models using the 6 years (2002-2007) of streamflow data obtained from the National Hydro Power Corporation (NHPC). Some statistical tests have been performed on the developed series in order to decide the best synthetic series generated, so that the best series can be used for deriving optimal operating policy for LSHE project.

6.2 Thomas-Fiering Model

Thomas-Fiering method is widely used for the generation of synthetic stream flow. It is a Markov Chain model which describes that there is a definite dependence of the flow of present time step on previous time step. For applying Thomas Firings method input data is generally transformed by using different methods like log transformation, power transformation and Box-Cox transformation (Box-Cox 1962) to have the input data in a normal distribution. In this study log transformation method is adopted to transfer the historical data. Raman and Sunil Kumar (1995) and Salas et al. (1985) used the same method for the transformation of data in their studies and found it to be quite efficient. Maass et al. (1970) presented that log transformed data has the advantage of eliminating occurrence of negative flows while generating synthetic streamflow. The recursive equation of Thomas Fiering model used for the study is give below:

$$q_{p+1,t} = q_{av,p+1} + r_{p,p+1}(\sigma_{p+1}/\sigma_p)(q_{p,t} - q_{av,p}) + \sigma_{p+1}(1 - r_{p,p+1}^2)^{1/2}\zeta_{p,t} \quad 6.1$$

where, p = period which may be of any length say 10 days or month;

t= year; $q_{av,p}$ = mean of the historical streamflow series for period p(current period);

$q_{av,p+1}$ = mean of the historical streamflow series for period $p+1$(next period);

σ_p and σ_{p+1} = standard deviation of historical series of period

p and $p+1$ respectively;

$r_{p,p+1}$ = correlation between period p and $p+1$ of historical series;

$\xi_{p,t}$= independent standard normal random variable;

$q_{p+1,t}$ = logarithmic predicted value of period $p+1$ for a particular t.

The $q_{p+1,\,t}$ values thus generated are then transformed to periodical flow by using the following relationship;

$$Q_{p+1,t} = \exp(q_{p+1,t}) \quad 6.2$$

Using the above model 100 years synthetic streamflow series of different time steps are generated for the LSHE project.

6.3 Artificial Neural Network (ANN)

Application of ANN is gaining popularity in numerous fields including business, aerospace, automotive, banking, credit card activity checking, defense, electronics, entrainment, finance, industry, manufacturing, medical, oil and gas, robotics, speech, security, telecommunication and transportation etc. It has been efficiently applied to solve many problems of water resources and hydrology.

6.3.1 Fundamentals of ANN

The Artificial neural networks (ANN) are commonly pronounced as 'Neural Network' consists of simple elements operating in parallel. These elements are analogous to biological nervous systems, the term 'Node' of biological system replaced by 'Neuron' and 'Synaptic' connections is substituted with 'Network'. Feedforward neural network used in the present study is the widely used neural network architecture. Feedforward network structure consists of various layers. Network neurons arranged in a group are called layers. The neurons in a layer are connected to the adjacent layer by the means of weights; the network function is determined largely by the connections between elements. But in the same layer, these neurons do not have any connection. The network is having one input layer with some neurons where input data is fed to the network, one or more hidden layer (s) where data is processed and one output layer from where results are produced for the given input. The neurons in hidden layer and output layers are called the activation function. The output is produced based on the weighted sum of the input signals entering into the neurons. Input received in any layer is the output of the preceding layer, hence the input signals propagate in the forward direction layer-by layer; that's way the architecture is called feedforward neural network. The network architecture is presented in Fig 6.1. The information processing through the neurons in each layer are adjusted by network weights, so the control of passing signals can be achieved. When the network weight is modified the information passed through the network also changes and so the network output. The weights keeps on adjusting in order to get desired output, this process is called learning. The learning processes may be of two types; one supervised and another is unsupervised. After several iterations when the network is learned enough the network is considered to be trained. After the enough learning of network the weights are fixed validation should then be performed using different kind of data set which ANN has not come across. Outcome of the validation makes conformation for the retraining of the network or to use the same network for the purpose.

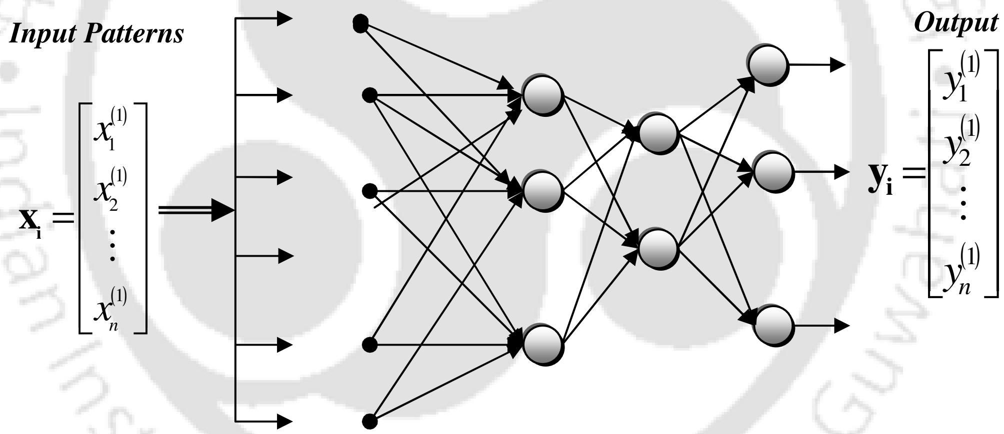

Fig. 6.1a Feed-forward neural network with three-layer

In this study feedforward neural network is adopted with supervised learning. Back-propagations are most commonly used learning algorithm in feedforward neural network. Input is applied to the network through input neurons, number of neurons in input layer is same as number of input elements. The number of neurons in the hidden layer is decided after extensive trial and error. The activation function is used to express the non-linear relationship between the input and output. It is normally a monotonic non-decreasing function and differentiable everywhere for x values.

Freeman proposed that a range of x values from 0.1 to 0.9 should be used for practical purposes. This range is adopted in this study. Thus, the input data and output data is being scaled (during training of ANNs) to fall under the above-mentioned range. A linear scaling is used here as in Hines (1997). Scaling input data and output data has the advantage on the speed of convergence of the system and it gives each input equal importance and prevents premature saturation of the activation function (Hines, 1997). The activation function most commonly used is unipolar sigmoid function, which is non-linear continuous function between 0 and 1, and is represented as below. The output y_i from hidden layer becomes as given in equation 6.3:

$$y_i = f(x) = \frac{1}{1+e^{-x}} \qquad 6.3$$

where,

$$x = \sum \left(W_{ji} x_i + b_i \right) \qquad 6.4$$

w_{ji} = the weight of the connection joining the j^{th} neuron in the hidden layer with the i^{th} neuron in the input layer,

x_i = the value of the i^{th} neuron in the input layer, and

y_j = the output from the j^{th} neuron in the hidden layer

b_j = bias for the j^{th} neuron in the hidden layer

The output of neurons in the output layer is computed similarly. The working principle of feed forward network is available elsewhere (Zurada 1999).

a) Training of Network

The training process involves giving known input and target to the network and adjusting internal parameters viz. weight and biases based on the performance measure and other network parameters. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Generally, neural networks are adjusted, or trained, in order to achieve a particular target for a give output.

The Back-propagation algorithm works iteratively; first step of it is to apply the example to the network, then network produces some outputs based on the initial weights. The network output is then compared with the target known output and mean square error is computed. This computed error value is propagated though network and weights are changed correspondingly in each layer. Weights are again adjusted in order to reduce the error. For each iteration the same process is repeated until the error value falls below the pre-defined threshold value at this moment network is said as well 'learned network'. The generalized delta rule, popularly known as backpropagation algorithm (Rumelhart et al. 1986), for training the network is embodied in the following steps:

(1) Start with an assumed set of weights. The initial weights are initialized with the help of a random number generator and they are very close to zero.

(2) Apply an input vector to the network and calculate the corresponding output values.

(3) Compare the computed outputs with the correct outputs and determine a measure of the error.

(4) Determine the amount by which each weight needs to be changed. In the backpropagation algorithm, the weight associated with a neuron is adjusted by an amount proportional to the strength of the signal in the connection and the total measure of the error.

(5) Apply the corrections to the weights. The total error at the output layer is then reduced by redistributing this error backward through the hidden layers until the input layer is reached.

(6) Repeat the item 1-5 with all the training vectors until the error for all vectors in the training set is reduced to an acceptable value.

In this study training has been carried out using the backpropagation algorithm, which is a gradient descent procedure. The algorithm updates the interconnection weights w_{ji} using the derivatives δ_i as follows:

$$\Delta w_{ji}(s) = -\eta \delta_j x_i + \alpha \Delta w_{ji}(s-1) \qquad 6.5$$

where, η = learning rate;

α = the momentum factor;

s= epoch/training iteration number,

δ= a factor depending on whether neuron j is an output neuron or a hidden neuron (Rumelhart and Mcclelled 1987). A training iteration is defined as one cycle of training using the considered pattern set. For the j^{th} neuron in the output layer

$$\delta_j = \left(\frac{df}{dnet_j}\right)\left[y_j^{(t)} - y_j\right] \qquad 6.6$$

in which $y_j^{(t)}$ = desired response; y_j = output response from NN; f = activation function; and net_j = (,i.e., weighted sum of input into the neuron j).For the j^{th} neuron in the hidden layer

$$\delta_j = \left(\frac{df}{dnet_j}\right)\sum_q w_{qj}\delta_j \qquad 6.7$$

in which q= number of neurons in the output layer; δ_q = already computed for the q^{th} neuron in the output layer. Similarly changes in the bias for j^{th} neuron are given by:

$$\Delta b_j(s) = \eta \delta_j + \alpha \Delta b_j(s-1) \qquad 6.8$$

The performance measures used in this study for the evaluation of neural network are mean square error (MSE) and mean relative error (MRE). They are defined by:

$$MSE = \frac{1}{2}\sum_q \sum_{j=1}^{p} (y_j^{(t)} - y_j)^2 \qquad 6.9$$

$$MRE = \frac{1}{pq}\sum_{q}\sum_{i=1}^{p}\left(\frac{\left|y_j^{(t)} - y_j\right|}{y_j^{(t)}}\right)100 \qquad 6.10$$

Where, $y_j^{(t)}$ = standardized target value for pattern j, y_j = output response from the network for pattern j, p = total number of training pattern; q = number of output nodes.

The MSE and MRE are good measures for indicating the goodness of fit at high and moderate output values, respectively (Karunanithi et al, 1994).

b) Network Selection

Selection of best network is relatively difficult task which involves extensive trial and error procedure. The final section of network parameters and architecture, learning rate η (eta) and momentum factor α (alpha) values are carried out after examining several combinations. The effectiveness and convergence of training depends significantly on the value of learning rate. If it is too high, then the search may miss a valley in the error surface. On the other hand if it is too small, the convergence will be very slow (Chandramouli and Raman 2001). The momentum factor α (alpha) is generally accelerates the convergence. The learning rate η and the momentum factor α values are decided after examining different combinations. The number of neurons in the hidden layer of the neural network is finalized after a trail an error procedure using different combinations of learning rate and momentum factor. Burian et al. (2001) stated that typically the generalization of prediction and accuracy of an application increases as the number of hidden neurons decreases; as the number of hidden neurons increases, there is a corresponding increase in the number of parameters describing the approximating functions. As number of the neurons increases in hidden layer the trained ANN becomes more specific to the training data. Number of neurons in hidden layer is selected after the extensive testing procedure with different combination of neurons in hidden layer.

6.3.2 Synthetic Stream Flow Generation Using ANN

Synthetic streamflow generation is carried out for the LSHE project using ANN approach. The main elements of the ANN model for the study are; ANN component and the random component. The first component supports to generate the synthetic series while the second one is added to the ANN generated series to eliminate the possibility of generating same series repeatedly.

a) Developing ANN Component

In the present study, three layer feed-forward neural networks is selected. The sigmoid transfer function is used in hidden layer and output layer which generate the output value ranging from 0 to 1. The illustrative neural network architecture is shown in Fig.6.1. In this study different number of hidden neurons and different number of input variables have been used for generating streamflow of different time step.

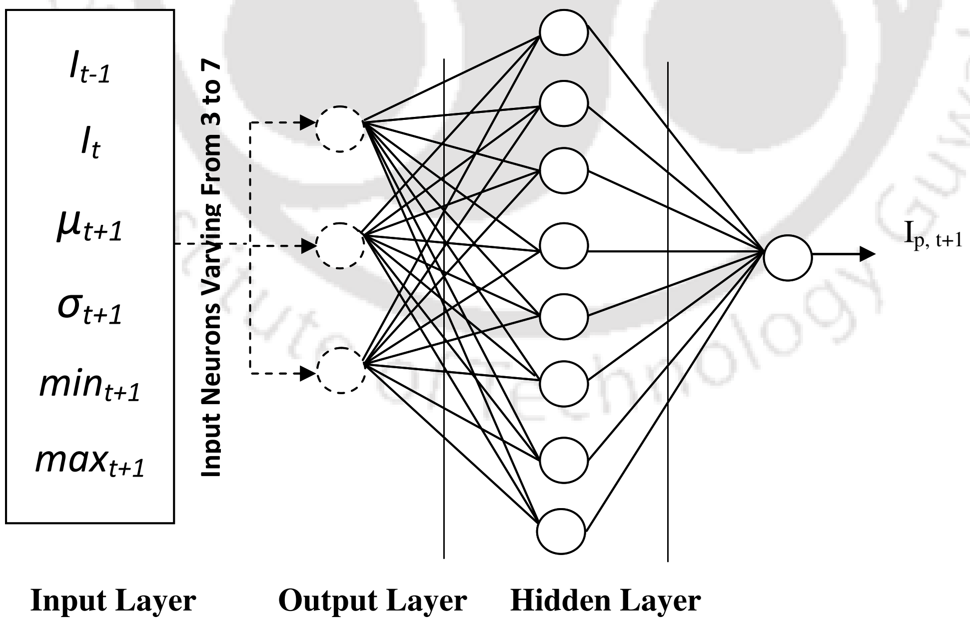

Fig.6.1b ANN base synthetic streamflow generation model (ANN)

Inflow data of the six years (2002-2007) for the LSHE project has been used in this study, out of which, 4 years data is used for the training of the network and 3 years overlapped data are used for the testing of the network. Since, there are 12 periods for monthly series, the value of the mean, standard deviation, average time rate of change of discharge in different periods of the series (gradient), maximum and minimum value of historical flow repeats in a cycle of 12 periods. The most common and popular multi-layer network used in training algorithm is Back Propagation (BP) (Rumelhart et.al., 1986 and Hagan et.al., 1996) adopted in this study. It is found that a model working well for a monthly streamflow series does not perform well for a series having smaller time step discretization such as ten daily, eight daily, six daily, five daily and daily. Therefore it was decided to attempt different model for different time step discretization.

(i) Time Step Discretizations and Input Selection for Streamflow Generation

Non linearity of streamflow series increases with decrease in the length of time step over which the values are averaged. Therefore different models having different number of input parameters have been tried to obtain the best possible model for a particular time step length. Different models have been tried in this study by using different combinations of input parameter from the following set of input parameters; Streamflow of current period (I_t), Streamflow of previous period (I_{t-1}), mean (μ_{t+1}) and standard deviation (σ_{t+1}) of historical streamflow of next period, minimum value of inflow from the given historical record (min_{t+1}) and maximum value of inflow from the given historical record (max_{t+1}), average time rate of change of discharge of the series (G_{t+1}). Table-6.1 shows the combinations of input parameters used in different models tried in this study.

Table 6.1 Different models with respect to time step discretization and input variables

Time Step	Mod	Input parameters
Monthly discretization	ANN30D1	I_t, μ_{t+1} and σ_{t+1}
	ANN30D2	I_{t-1}, I_t, μ_{t+1} and σ_{t+1}
Ten daily discretization	ANN10D1	I_t, μ_{t+1} and σ_{t+1}
	ANN10D2	I_{t-1}, μ_{t+1} and σ_{t+1}
	ANN10D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}
	ANN10D4	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1}
	ANN10D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}
	ANN10D6	I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
Eight daily discretization	ANN08D1	I_t, μ_{t+1} and σ_{t+1}
	ANN08D2	I_{t-1}, μ_{t+1} and σ_{t+1}
	ANN08D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}
	ANN08D4	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1}
	ANN08D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}
	ANN08D6	I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
Six daily discretization	ANN06D1	I_t, μ_{t+1} and σ_{t+1}
	ANN06D2	I_{t-1}, μ_{t+1} and σ_{t+1}
	ANN06D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}
	ANN06D4	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1}
	ANN06D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}
	ANN06D6	I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
Five daily discretization	ANN05D1	I_t, μ_{t+1} and σ_{t+1}
	ANN05D2	I_{t-1}, μ_{t+1} and σ_{t+1}
	ANN05D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}
	ANN05D4	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1}
	ANN05D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}
	ANN05D6	I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
	ANN05D7	I_{t-1}, I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
Daily discretization	ANN01D1	I_t, μ_{t+1} and σ_{t+1}
	ANN01D2	I_{t-1}, μ_{t+1} and σ_{t+1}
	ANN01D3	I_t, μ_{t+1}, σ_{t+1} and G_{t+1}
	ANN01D4	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and G_{t+1}
	ANN01D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}
	ANN01D6	I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and
	ANN01D7	I_{t-1}, I_t, μ_{t+1}, σ_{t+1}, min_{t+1}, max_{t+1} and

(ii) Training and Testing

Training was initial carried out for 2500 iterations but it was found that there was no significant improvement in MSE value after 2000 iteration, rather the time requires to train the network was increasing, hence the network is trained up to 2200 epochs. The MRE value for the testing and training was found separately and network is selected considering lowest MRE and MSE values for the particular number of neurons in hidden layer. In this study, best model has been decided by varying numbers of neurons in hidden layer from 3 to 10. For each network different combination of the learning rate η = 0.00, 0.01, 0.02, 0.04, 0.05, 0.07, 0.09, 0.1, 0.2, 0.3, 0.5, 0.7 and 0.9 and momentum factor α = 0.01, 0.02, 0.04, 0.05, 0.07, 0.09, 0.1, 0.2, 0.3, 0.5, 0.7 and 0.9 has been tried for the final selection of model. The best value corresponding to different learning rate η and momentum factor α was found after extensive trial and error with different combination of η and α. Table-6.2 to Table-6.7 present the MSE and MRE values with different numbers of neurons in hidden layer.

Table-6.2 MSE and MRE values-ANN30D1

Neurons Hidden Layer (10 daily)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.040452	28.2546	0.0580	41.4286
4	0.038213	28.6033	0.0571	46.7165
5	0.037847	28.9926	0.0658	52.4647
6	0.038409	26.959	0.0799	54.3066
7	0.037871	30.7061	0.0687	52.9299
8	0.037848	25.3992	0.0709	52.8416
9	0.032074	22.6417	0.0637	55.9729
10	0.033522	32.9324	0.0700	56.0974

Table-6.3 MSE and MRE values-ANN10D1

Neurons - Hidden Layer (Monthly)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.045185	61.0128	0.0566	44.9493
4	0.042522	51.9333	0.0899	69.8267
5	0.039036	54.2617	0.0776	56.7994
6	0.035631	47.2419	0.0669	48.2199
7	0.048346	63.9022	0.0922	67.3016
8	0.028801	39.6045	0.0636	40.5137
9	0.032503	45.5739	0.0704	58.0878
10	0.033765	43.5303	0.0728	47.8197

Table -6.4 MSE and MRE values-ANN08D1

Neurons-Hidden Layer (8 daily)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.036986	20.8422	0.0492	35.6744
4	0.035716	20.6769	0.0507	33.5632
5	0.035597	19.6389	0.0495	34.1005
6	0.035475	19.9275	0.0482	32.6109
7	0.034504	19.4594	0.0465	31.5748
8	0.033317	18.9124	0.0477	32.7274
9	0.032049	19.6566	0.0421	30.6584
10	0.032326	19.3615	0.0426	30.5810

Table-6.5 MSE and MRE values-ANN06D3

Neurons Hidden Layer (6 daily)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.030175	21.056	0.0373	38.4291
4	0.030748	20.5256	0.0373	34.8625
5	0.029254	19.9299	0.0366	34.7174
6	0.029636	20.3271	0.0370	34.8791
7	0.028346	19.9857	0.0366	33.0956
8	0.029192	19.3799	0.0392	31.2638
9	0.028717	19.5433	0.0342	34.9841
10	0.027825	19.4225	0.0363	31.2843

Table-6.6 MSE and MRE values-ANN05D6

Neurons-Hidden Layer (5 daily)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.031445	22.0509	0.0339	38.805
4	0.030142	21.7799	0.0316	39.1053
5	0.030599	20.0876	0.035	36.8486
6	0.029210	21.9088	0.0339	36.9155
7	0.029091	20.5476	0.0346	36.1137
8	0.028419	20.2891	0.0345	36.3516
9	0.028971	21.1404	0.0349	37.4184
10	0.027347	19.6500	0.0344	35.4664

Table-6.7 MSE and MRE values-ANN01D5

Neurons-Hidden Layer (daily)	Training		Testing	
	MSE	MRE	MSE	MRE
3	0.009259	20.063	0.0139	39.8489
4	0.009062	18.3655	0.0138	39.0409
5	0.008775	16.8718	0.0136	40.1766
6	0.008881	17.8888	0.0132	33.5179
7	0.008848	18.1755	0.0136	36.9351
8	0.008806	17.3207	0.0137	37.756
9	0.008123	16.6544	0.0133	34.8237
10	0.008639	17.4512	0.0134	36.0884

Each table gives different network parameters for model which performs better on the basis of input parameters for different time discretization.

b) Synthetic Streamflow Generation

In this study trained and tested network was used to generate series of synthetic streamflow. It was found that after several iterations the network was producing the repeated streamflow series. The statistical analysis of residual series shows that, it can be adequately modeled as normally distributed and crosscorrelated series with zero mean and unit standard deviation (Ochoa-Rivera et.al.2007). Therefore, it is very important to introduce random component in the streamflow generation model to prevent the network from generating repetitious sequence of streamflow. A small random component calculated on the basis of the standard deviation of the observed streamflow is added to the output produced by the network (Ahmed and Sarma 2007). Thus repetitive generations of streamflow were handled by introducing a random component $\xi_t\sigma_t$ in the model. Where, ξ_t is an independent standard normal random variable with mean zero and variance unity, σ_t is the standard deviation of observed streamflow of the corresponding month. Synthetic streamflow series of hundred years are generated by feeding the known value of inflow of previous period, inflow of current period, periodical mean of the historical flow of next period and periodical standard deviation of the historical flow of next period, maximum and minimum of historic flow of next period and average time rate of change of discharge in different periods of the series of flow. The output of the model will be the predicted inflow of the succeeding period and it will serve as input for the next iteration. If negative flow occurs during synthetic streamflow generation, would be replaced by the minimum value of the historic flow for the particular period (Ahmed and Sarma 2007).

6.4 Comparison of Results of ANN, Thomas-Fiering and Actual Streamflow Series

Hundred years' synthetic streamflow series has been generated using Thomas-Fiering model and ANN-based models for different combinations of inputs. The results are compared with the observed streamflow series of six years (2002-2007) on the basis of statistical parameters; periodical mean, periodical standard deviation and skewness of the generated and actual observed series and presented in the Table-6.8. The best ANN model for each of the different time discretization has been selected based on the extensive trial carried out with several combinations of input parameters. The Table-6.8 gives the information of each of those models along with the corresponding parameter for which they are working best. Several trials have been made to work out the best ANN model for different time step discretization by considering different number of hidden neurons and input parameters.

Trial made for monthly model is detailed in Table- 6.1. The ANN30D1 with 8 neurons in hidden layer, momentum factor α = 0.05 and learning rate η = 0.05 was found to be the best. The results showing the comparisons of ANN and Thomas-Fiering models with the observes mean monthly time series and standard deviation of observed monthly time series are presented in Fig 6.2 and Fig 6.3 respectively. It is clear from the curve that synthetic streamflow generated by ANN series though generates slightly higher value in case of periodical mean, periodical standard deviation of the generated series is quite close to the actual series. The skewness value of the series generated by ANN30D1 is found closer to the skewness value of actual series in comparison to that of the Thomas-Fiering model.

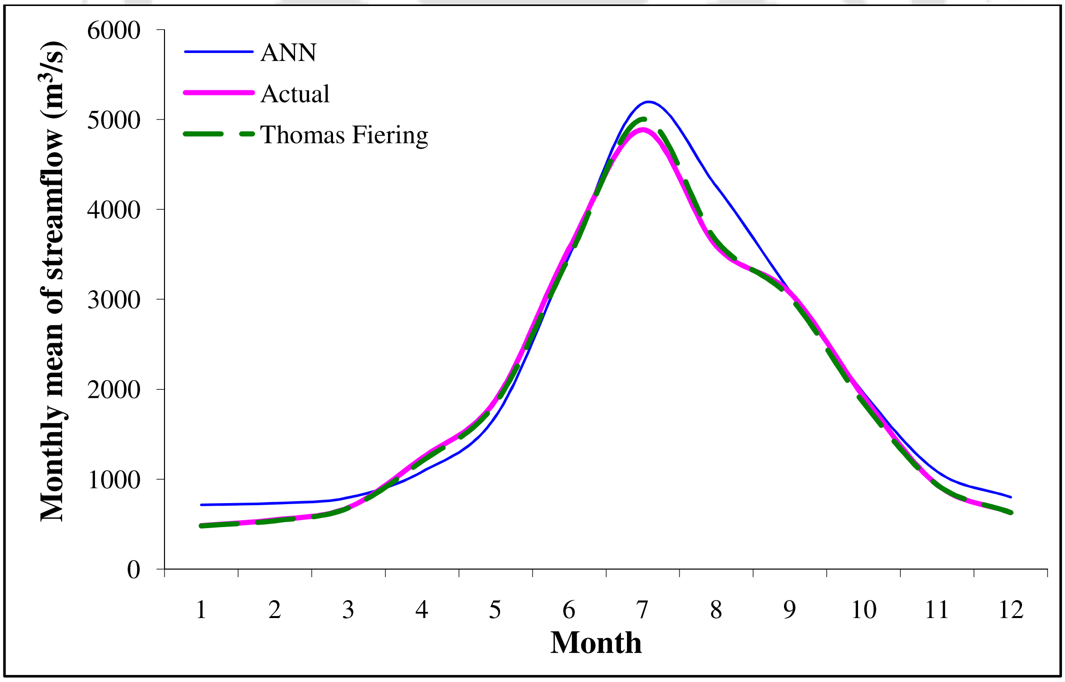

Fig.6.2 Mean of synthetic series –ANN30D1

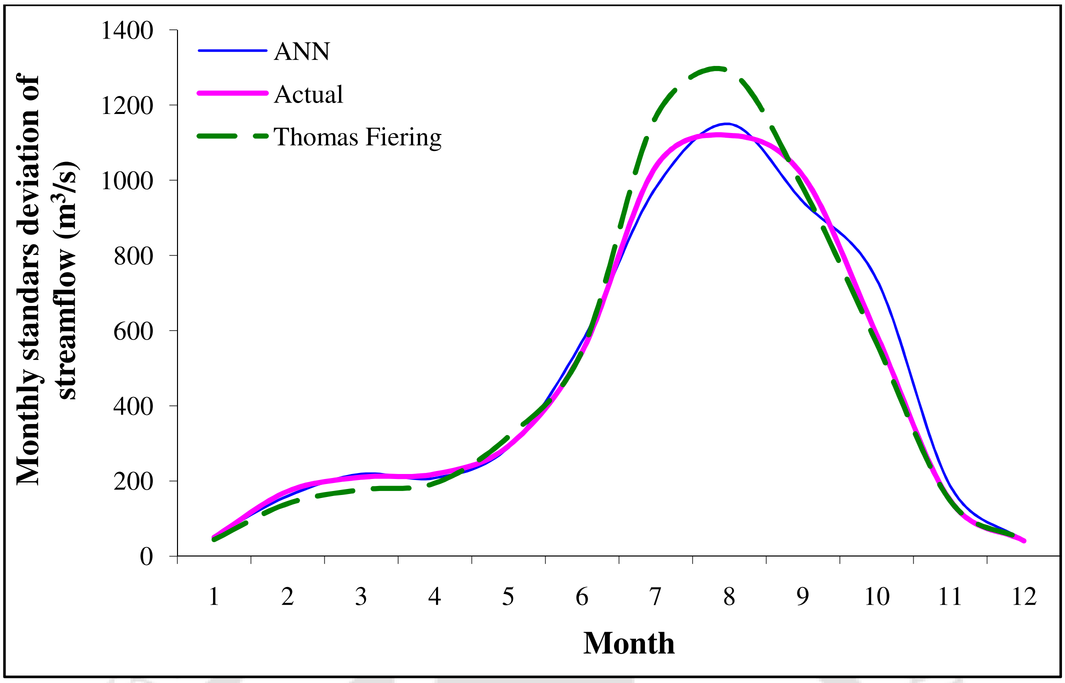

Fig.6.3 Standard deviation of synthetic series –ANN30D1

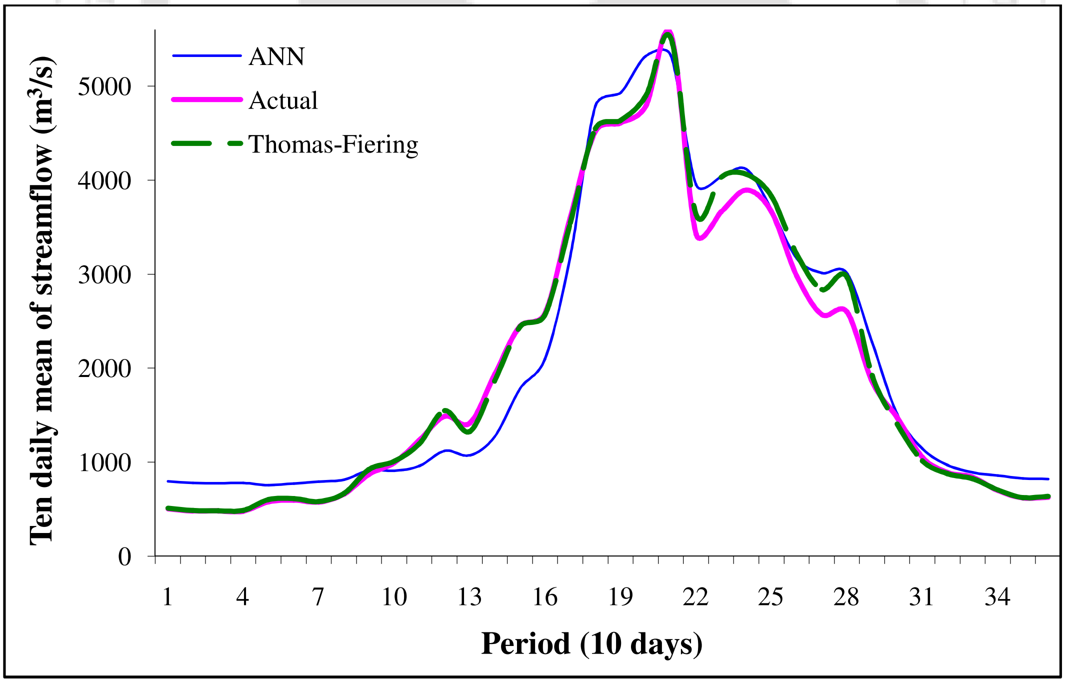

Fig.6.4 Mean of synthetic series –ANN10D1

In case of the ten daily ANN models, ANN10D1 is found best. It has 3 neurons in hidden layer (Table 6.3) with $\alpha = 0.5$ and $\eta = 0.05$. Fig 6.4 and Fig 6.5 are the plots showing the comparisons of ANN10D1 and Thomas-Fiering with the actual ten daily series for mean and standard deviation of the synthetic series. The results depicts that both ANN generated series and Thomas-Fiering model generated series are in good agreement with the actual series in respect of periodical mean. In respect of standard deviations and skewness of the series ANN10D1 outperform the Thomas-Fiering model.

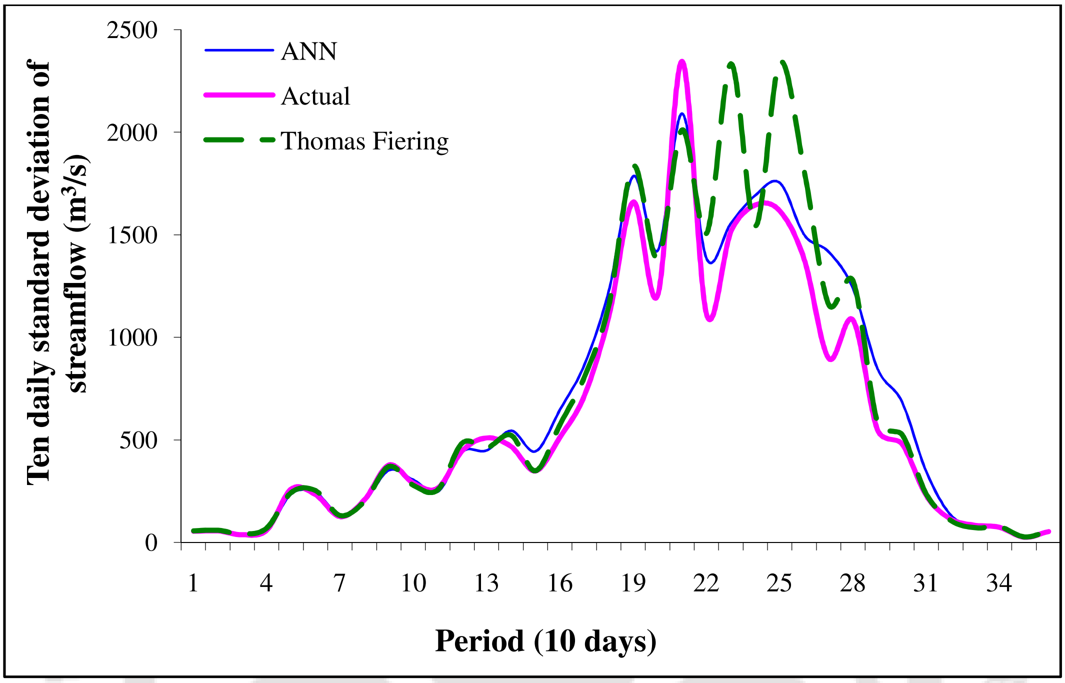

Fig.6.5 Standard deviation of synthetic series –ANN10D1

It has been found from the Table 6.1, Table 6.4 and Table 6.8 that the ANN08D1 having 10 neurons in hidden layer, α = 0.02 and η = 0.04 is performing better among others ANN models for eight daily time step. The comparative results are presented in Fig 6.6 and Fig 6.7; periodical mean of the ANN generated series has been found to give slightly lower values in the pre-monsoon period and slightly higher value in the dry period as compared to actual series, but it follows quite well to the observed series in case of periodical standard deviation. As observed in the previous cases regarding Thomas-Fiering model, here also it can capture the periodical mean very well but it fails to capture the periodical standard deviation. The skewness coefficient of the entire series generated by ANN08D1 is relatively close to skewness value of the actual streamflow series as compared to the skewness value of the series generated by Thomas-Fiering model.

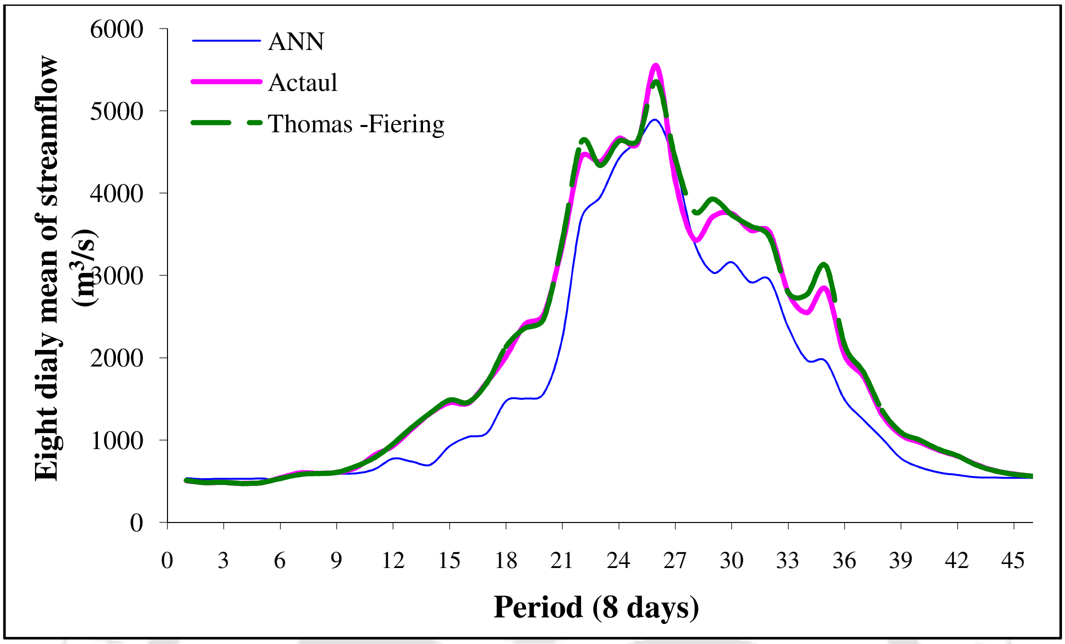

Fig.6.6 Mean of synthetic series –ANN08D1

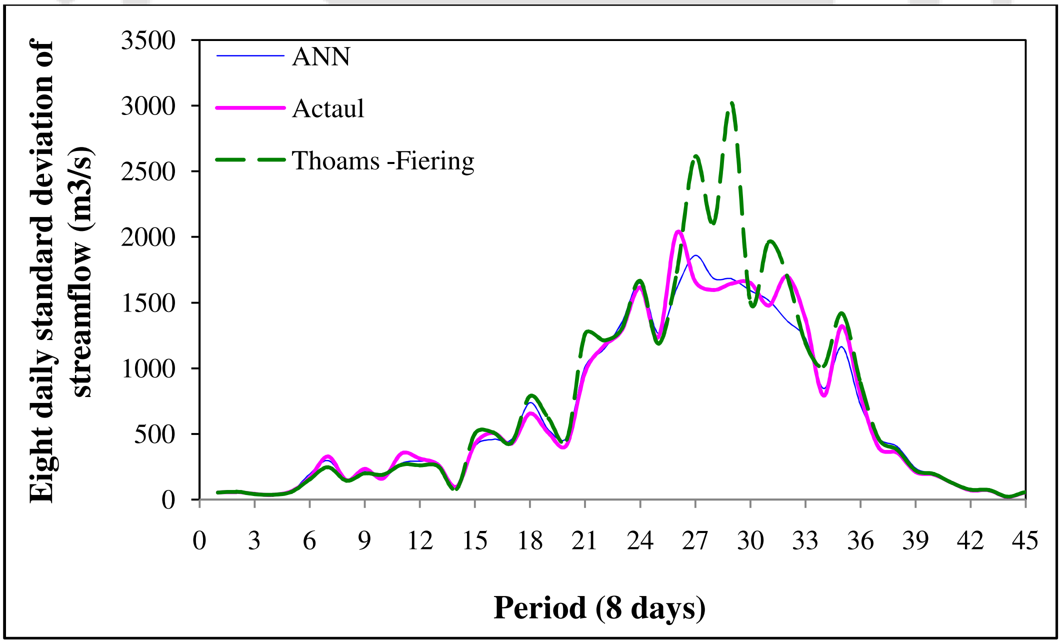

Fig.6.7 Standard deviation of synthetic series –ANN08D1

For six daily time step discretization the ANN06D3 model having four input parameter (Table 6.1), 8 neurons in hidden layer, α = 0.9 and η = 0.09 found to be the most efficient as compared to others. The comparisons of mean and standard deviation of each period of the series are shown in Fig 6.8 and Fig 6.9.

The results reveals that though the periodical mean of the series generated by Thomas–Fierings methods follows good except for the period during second seasonal peak i.e. during months of August and September, the series generated by ANN predicts relatively low values during pre monsoon period. On the other hand the periodical standard deviation of series generated by ANN is in close agreement with the actual series while the series generated by Thomas-Fiering model gives very high values. Moreover, the skewness value of the whole series generated by Thomas Fiering is also found high than the skewness of the actual series as compared to ANN (Table- 6.8).

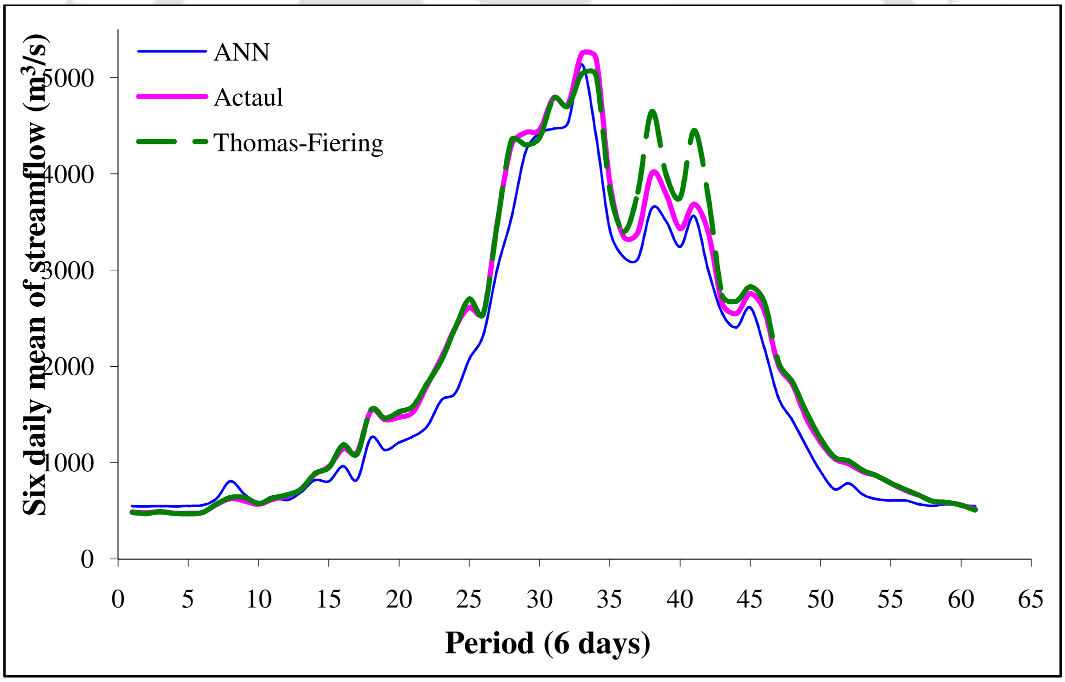

Fig.6.8 Mean of synthetic series –ANN06D3

Fig 6.10 and Fig 6.11 gives a comparison of the synthetic series generated by Thomas-Fiering’s method and ANN method for five daily time step. The ANN05D6 model having 10 neurons in hidden layer, α = 0.9 and η = 0.04 performs better as compared to other models.

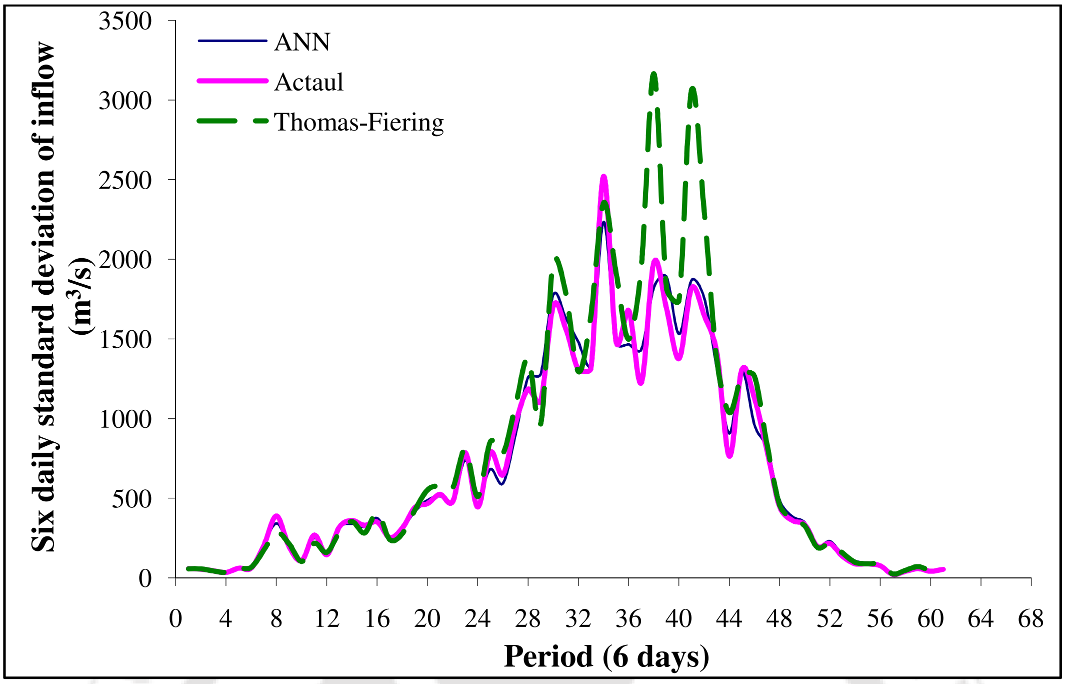

Fig.6.9 Standard deviation of synthetic series –ANN06D3

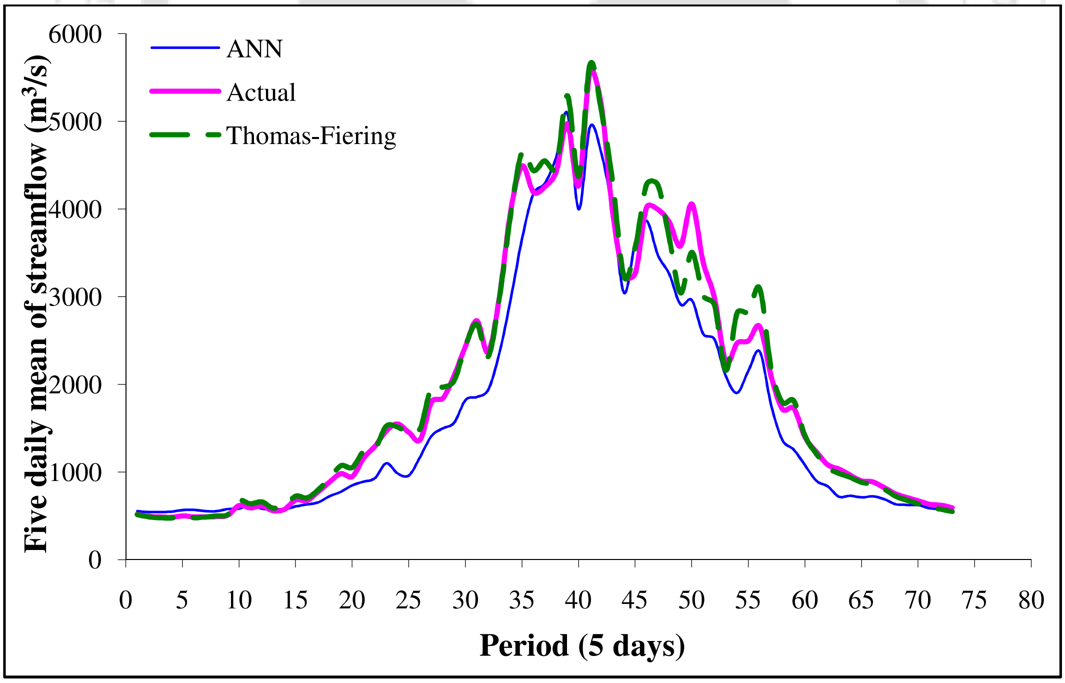

Fig.6.10 Mean of synthetic series –ANN05D6

The periodical mean of series generated by ANN05D6 gives marginally low values as compared to actual observed series while Thomas-Fiering generated series follows quite well to the actual series.

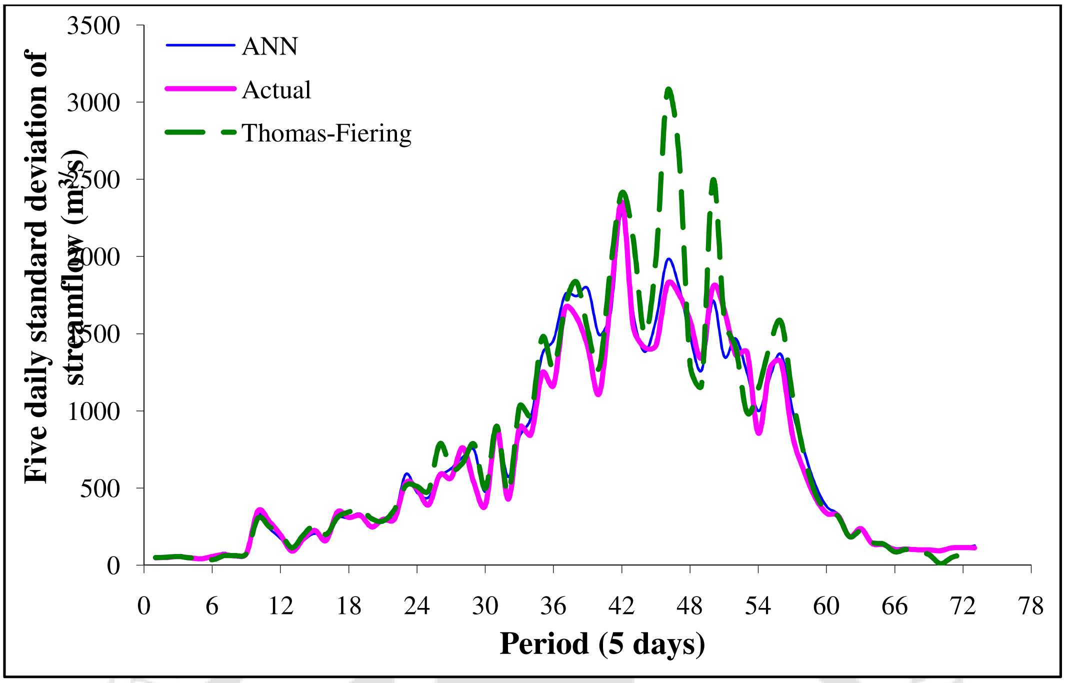

Fig.6.11 Standard deviation of synthetic series –ANN05D6

In case of periodical standard deviation ANN05D6 follows the actual series far better as compared to Thomas-Fiering generated series. From the Table 6.8 it is clear that the skewness of whole series generated by ANN05D6 is quite close to the skewness value of the actual series.

For the daily time step discretization, the result of the both model are shown in Fig 6.12 and Fig 6.13 respectively. The periodical mean of series generated by ANN01D5 follows well in lean season; it gives rather low values in the beginning as well as end of wet season and high values in peak wet season as compared to actual observed series. On the contrary Thomas –Fiering is found better in case of periodical mean. The comparisons of the periodical standard deviation shows that most of the time ANN01D5 is quite close to actual series except for a few periods.

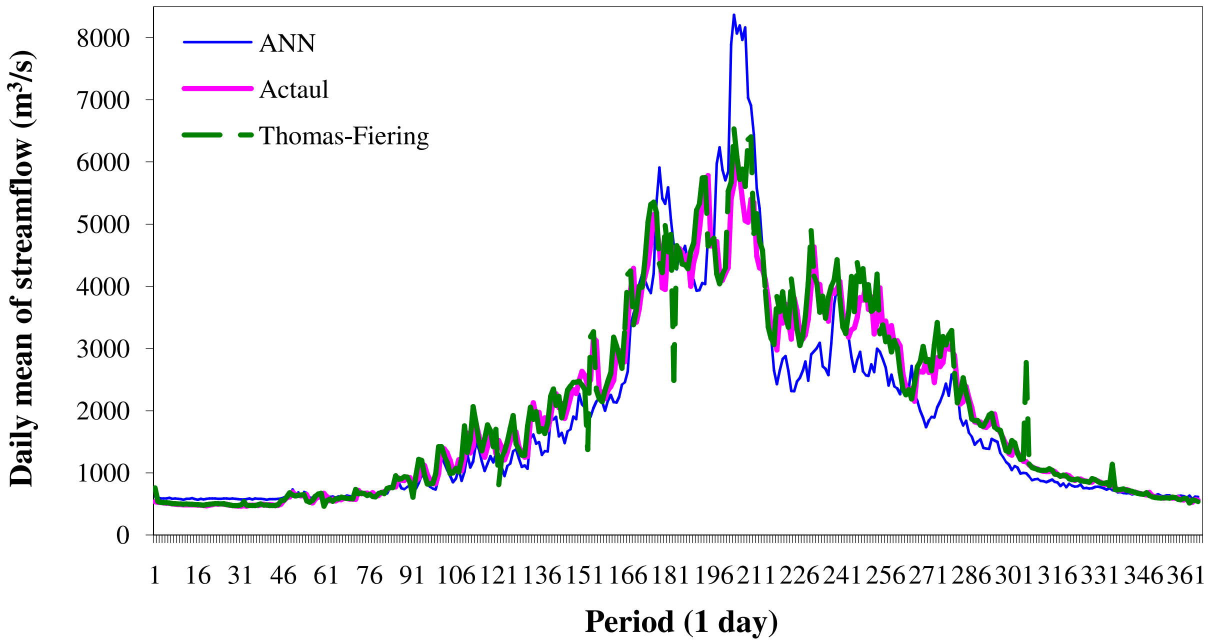

Fig 6.12 Mean of synthetic series -ANN01D5

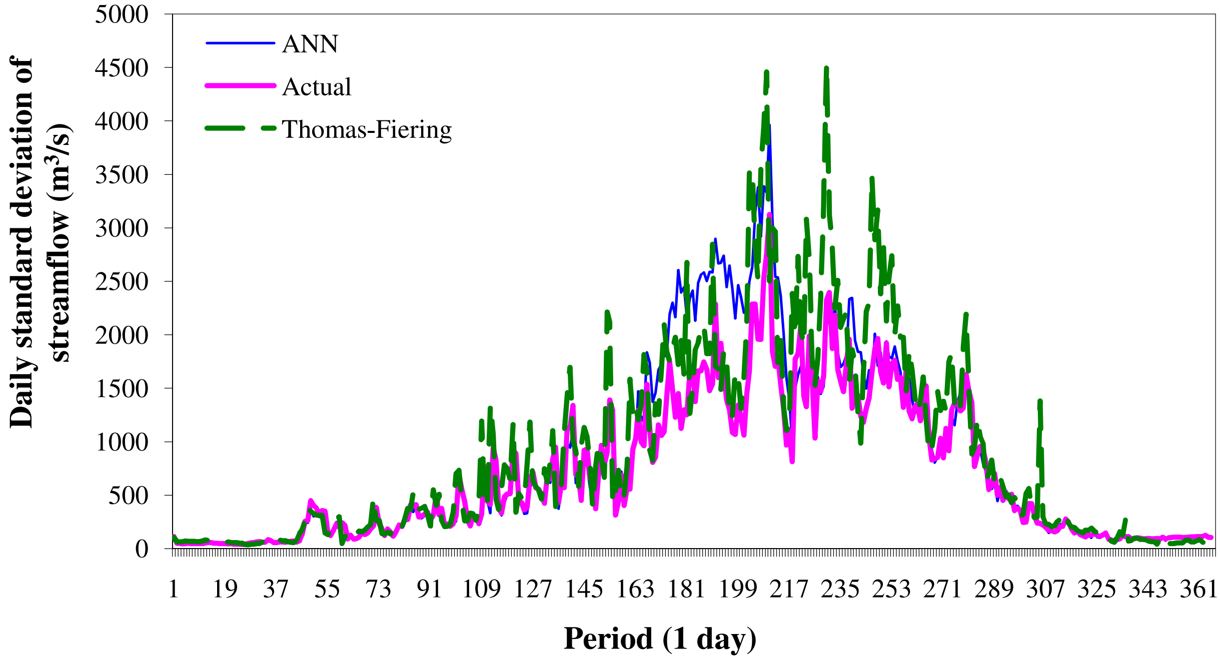

Fig.6.13 Standard deviation of synthetic series –ANN01D5

In this case the skewness value of the series generated using ANN01D5 model is also closer to the value of actual historical series as compared to Thomas-Fiering model. The best models for each time step discretization and their network as well as input parameters are summarized in the Table 6.8.

Table 6.8 Different ANN models and their selection parameters

Different ANN Models Selected on The Basis of Different Parameters											
ANN Model for Different Time Step	**Best Input Parameters**	**Number of Neurons in hidden Layer**	**Learning Rate**	**Momentum Factor**	**Training**		**Testing**		**Skewness of the Series**		
					MSE	**MRE**	**MSE**	**MRE**	**Actual**	**Thom-as Fiering**	**ANN**
ANN30D1	I_t, μ_{t+1} and σ_{t+1}	8	0.05	0.05	0.0288	39.6045	0.0636	40.5137	1.3584	1.7089	1.4308
ANN10D1	I_t μ_{t+1} and σ_{t+1}	3	0.05	0.50	0.0405	28.2546	0.0580	41.4286	0.9685	1.1984	1.0925
ANN08D1	I_t, μ_{t+1} and σ_{t+1}	10	0.04	0.02	0.0323	19.3615	0.0426	30.5810	1.3443	2.1950	1.6550
ANN06D3	I_t, $\mu_{t+1,}$ σ_{t+1} and G_{t+1}	8	0.09	0.90	0.0292	19.8986	0.0392	31.6238	1.3548	2.0833	1.9310
ANN05D6	I_t, μ_{t+1}, σ_{t+1}, $min_{t+1,}$ max_{t+1} and G_{t+1}	10	0.04	0.90	0.0318	19.6500	0.0344	35.4664	1.3703	1.9290	1.7120
ANN01D5	I_t, μ_{t+1}, σ_{t+1}, min_{t+1} and max_{t+1}	6	0.01	0.90	0.0165	20.8035	0.0200	33.5179	1.5373	1.7540	1.6320

Inflow of present time step (I_t), Mean of the historical series (μ_{t+1}) of next period, Standard deviation of historical series (σ_{t+1}) of next period, Minimum value of inflow from the given historical record (min_{t+1}), Maximum value of inflow from the given historical record (max_{t+1}) and Average time rate of change of discharge of the series (G_{t+1}).

6.5 Hybrid Model for Streamflow Generation

The increasing need of the accuracy in predicting time series inspired the researchers to develop model using the capability of different methods. Such models are popularly known as hybrid models. Zhang (2003) proposed a hybrid ARIMA and ANN model to take advantage of the two techniques and applied the proposed hybrid model to some real data sets. He concluded that the combined model can be an effective way to improving forecasts achieved by either of the models used separately. Jain and Kumar (2007) said that the results obtained from hybrid model suggest that the approach of combining the strengths of the conventional and ANN techniques provides a robust modeling framework capable of capturing the non-linear nature of the complex time series and thus producing more accurate forecasts. As such, the applicability of hybrid model has been gaining popularity in various sectors, its contribution in hydrology and water resources engineering is limited. In the past, limited studies (Rivera et al. 2002, Zhang, 2003, Jain and Kumar, 2007 Birkinshaw, et al., 2008, Ashrafzadeh and Rizi 2009) towards application of hybrid model has been documented, which reveals the efficiency of hybrid model by combining features of traditional and nontraditional techniques.

It is observed that Thomas-Fiering model gives better results during low flow period in terms of all the three statistical parameters considered in this study. On the other hand ANN model gives better results during monsoon period. In the present study an effort has been made to develop a hybrid model which inherits the quality of traditional Thomas-Fiering and ANN approach for the synthetic streamflow generation, to achieve the better level of accuracy. Therefore a hybrid model has been developed by utilizing capability of both these methods and a series having close resemblance with the observed series has been generated.

The model is tested through its application for the synthetic streamflow generation for ten daily time step in LSHE project. The numbers of period in a year for ten daily generations are 36, staring from January-I to December-III each month having three periods. The lean period flow is generated using Thomas-Fiering model while the wet period flow is generated using ANN model. The mathematical formulation of hybrid model is presented as below;

$$I_{p,t+1} = \begin{cases} q_{av,p+1} + r_{p,p+1}(\sigma_{p+1}/\sigma_p)(q_{p,t} - q_{av,p}) + \sigma_{p+1}(1-r_{p,p+1}^2)^{1/2}\zeta_{p,t} & (36\times Y)+0<t<(36\times Y)+16,\ (36\times Y)+32<t<(36\times Y)+37 \\ ANN & (36\times Y)+15<t<(36\times Y)+33 \end{cases}$$

where, Y = n (n =1,2,3,4..........3600), other symbols are same as stated earlier in equation 6.1.

The synthetic data generated by using the hybrid model has been used to develop the reservoir operation policies. The comparison of ten daily mean and standard deviation of hybrid and actual series is presented in the Fig 6.14 and Fig 6.15 respectively.

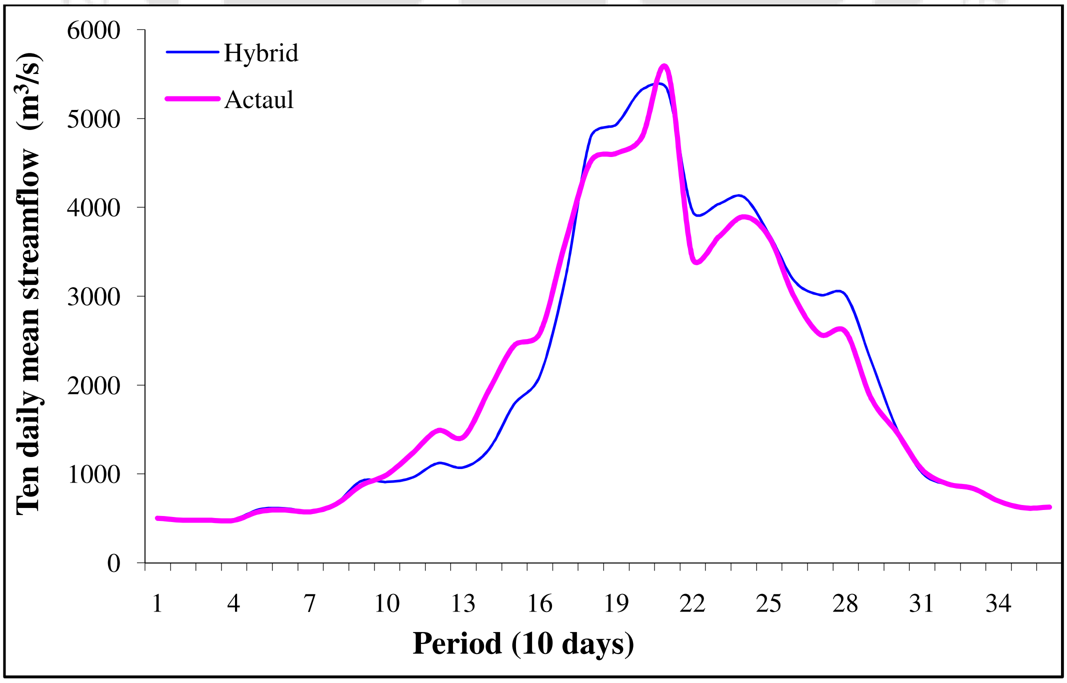

Fig.6.14 Mean of synthetic series –HYB10D

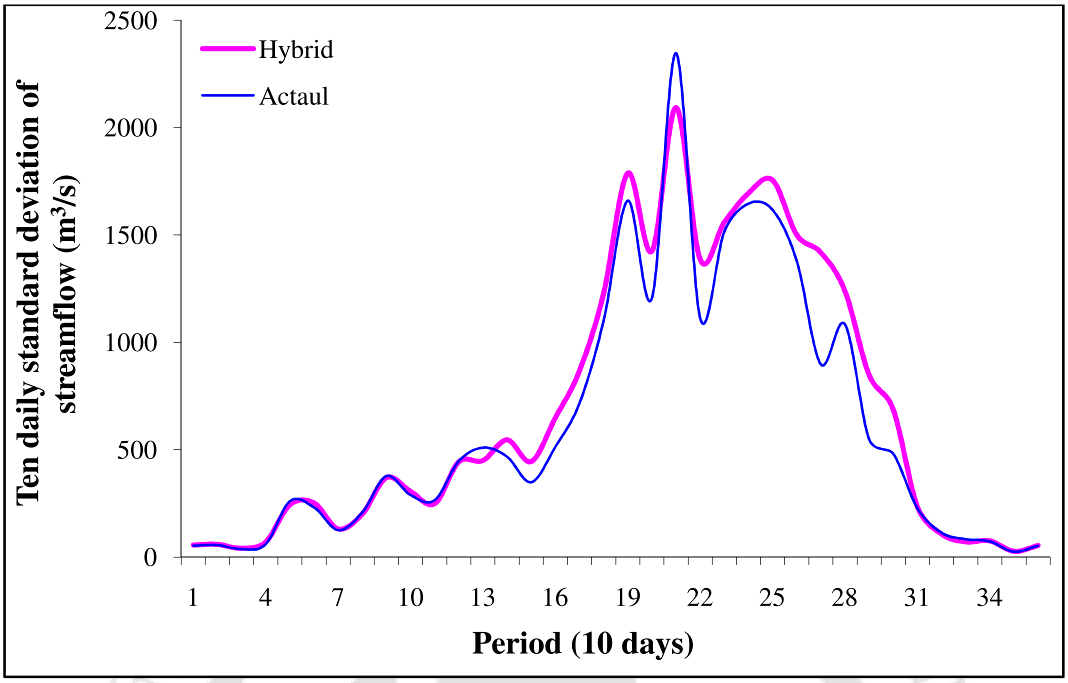

Fig.6.15 Standard deviation of synthetic series –HYB10D

The figure gives an idea that the ten daily mean of hybrid streamflow is following the actual series quite well in lean period though minor deviation in periodic mean is observed during wet period. Periodical standard deviation of the series is going quite well with actual streamflow series. Skewness of the hybrid streamflow series is also closer to actual streamflow series.

6.6 Conclusion

The performance of the ANN based model for the synthetic streamflow generation of the LSHE project with the limited data set has been investigated and its comparison is made with the Thomas-Fiering model considering some statistical parameters viz. (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series. `The influence of the time step discretization and selection of input parameters on the synthetic generation of streamflow has been evaluated using both the above said methods. Different models based on input variables and network parameters have been tried and the best model for each time step discretization has been evaluated using above said three statistical measures. The selection of input parameters plays an important role in the streamflow generation. It has been found from the result that the input parameters which have been working well for higher time step discretization models did not work well for the cases of smaller time step discretization. This study has revealed that for the Subansiri River the models ANN30D, ANN10D and ANN08D has been found to give better performance with three input parameters i.e. I_t, μ_{t+1} and σ_{t+1}.On the other hand ANN06D, ANN05D and ANN01D have performed better with input parameter sets $\{I_t, \mu_{t+1}, \sigma_{t+1}, G_{t+1}\}$, $\{I_t, \mu_{t+1}, \sigma_{t+1}, min_{t+1}, max_{t+1}, G_{t+1}\}$ and $\{I_t, \mu_{t+1}, \sigma_{t+1}, min_{t+1}, max_{t+1}\}$ respectively. Table 6.8 presents the best model, their input variables and the network parameters.

The results of the study depict that though periodical mean of the series generated by Thomas-Fiering follows well to the periodical mean of observed series as compared to the ANN model in most of the time discretizations, it gives relatively higher error in case of periodical standard deviation as compare to the ANN generated series. The skewness of the series generated by Thomas-Fiering and ANN models are compared, the skewness of the ANN generated series is found closer to the skewness of the observed streamflow series for each of these time step discretizations. Out the three performance criteria; (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series, ANN was found to be performing quite well for the periodical standard deviation and skewness coefficient of the series, while its performance for periodical mean, was also found satisfactory and within acceptable limit. The hybrid streamflow series is found to be performing better in lean seasons where the ANN series was lacking. In comparison of all three statistical parameters hybrid series is generating a series quite closer to the actual in terms of periodical mean and periodical standard deviation. The skewness value of the streamflow series generated by hybrid is also closer to the skewness value of the actual series. Based on the above analysis, it can be concluded that the hybriding of two methods is a better technique and can be regarded as an improved method of synthetic streamflow generation.

Chapter 7

Development of Reservoir Simulation Model

7.1 Introduction

Reservoir simulation is imperative technique to assess performance of an operating policy and to get a clear picture of the system behavior once it is put in to operation. Standard operating policy (SOP) decided for fulfilling objective of project is generally simulated by simulation model to examine its performance in respect of several performance criteria. Optimal operating policies obtained through optimization technique are also tested by simulation model to assess their performance. According to Warbs (1993), simulation is a process of representing a system with a set of mathematical equations. Several simulation models have been discussed in the state of the art review presented by Yeh (1985), Wurbs et al. (1985) and Wurbs (1991). Loucks and Beek (2005) presented the capability of the simulation of model for reservoir operation. A Reservoir Simulation Model (RSM) has been developed in this study using C-programming to visualize some important aspects of the River-Reservoir system when operated using a standard operating policy. RSM has been carried out to achieve the following objectives;

a. To visualize changes in the flow scenario downstream of the LSHE project.

b. To examine scope of flood moderation.

c. To estimate power production and to analyze pattern of power production.

d. To explore scope of minimizing diurnal variation through change of operating policy or by adopting structural measures.

It has been seen that diurnal variations downstream of any hydroelectric project usually goes unnoticed, though it may have serious long term impacts. Generally these impacts are not visible immediately after the dam construction therefore it does not get due attention. As such, a flow augmentation caused by operation of every Run-off-the River (RoR) project induces several environmental losses downstream. Few of such possible impacts are analyzed in this study and presented in the following sections of the chapter. Several mitigating measures to reduce the diurnal variation which helps to address possible environmental impacts up to certain extent are proposed in the chapter.

7.2 Development of Reservoir Simulation Model (RSM)

Visualizing reservoir operation using Reservoir Simulation Model is one of the best techniques to foresee the impact of a reservoir operation on the flow scenario downstream. In a hydropower projects with additional objective of flood control, it is very important to decide the periodical release so that the production of power can be achieved satisfactorily keeping the reasonable storage to check the flood situation downstream of the river. Meeting power demand of peak hours in the lean period generally becomes an objective of a hydropower project. This leads to significant diurnal variation downstream of the dam, which in turn leads to serious ecological problems. Supplying required flow in the lean period to prevent various environmental degradations at downstream can be kept as a constraint. Similarly, during the monsoon period the objectives of producing power and providing flood-cushion are always conflicting in nature. In this study a reservoir simulation model is developed with an objective to produce the target power demand of 2000 MW for the maximum possible duration in a day subject to the constraints of maintaining reservoir level at a certain elevation so as to have provision of flood cushioning. Reservoir operating policy considering these objectives and constraints has been used to simulate the reservoir operation for twenty six years using synthetic stream flow. General demand oriented reservoir operating policy is considered to simulate the reservoir operation for twenty six years using synthetic streamflow data. The scope of minimizing diurnal variation by different alternative means has been analyzed.

7.2.1 Data Used For the Study

1. Synthetic stream flow of twenty six years has been used as inflow series.

2. Relationship of Storage-Elevation and Area-Elevation as given in the previous chapter has been used.

3. Capacity constraint, minimum drawdown constraint, release constraint, target reservoir elevation etc., has been used as given in the previous chapter.

7.2.2 The Details of Various Aspects of the RSM Model are Described Below

1) Frictional head loss h_f *(m)* has been computed dynamically based on the actual discharge Q_2 (m^3/s) flowing through the system to produce 2000MW of power. Possibility of releasing Q_2 discharge has also been checked by comparing it with the maximum possible discharge Q_1 (m^3/s) through the given penstock diameter under the available head.

$$Q_2 = \frac{P}{\eta \times \rho \times g \times H_{nt}} \tag{7.1}$$

$$Q_1 = C_d (A\sqrt{2gH_{nt}}) \tag{7.2}$$

Actual Discharge Q_{dt} (m^3/s) is taken as the least of the Q_1 and Q_2

Where, P =power (W) i.e 2000×10^6 W

η=efficiency of turbine (0.9),

ρ = density *(kg/m^3) (~ 1000 kg/m^3* for water),

g = acceleration of gravity (*9.81 m/s^2*)

2) Available Net Head H_{nt} (m) at any time t is estimated based on elevation of reservoir El_t (m), elevation of normal tail race water El_{tail} (m) and head loss due to friction.

$$H_{nt} = El_t - El_{tail} - h_f \tag{7.3}$$

3) After the calculation of the H_{nt}, (m) minimum desired release at any time t (R_{td}) is computed by taking into account the peeking hour (p_k) power demand; 4 hours of peaking has been taken as minimum in this project.

$$R_{td} = \frac{36 \times Q_{dt} \times p_k}{10^3} \tag{7.4}$$

4) Maximum release for any time t (R_{tm}) is calculated considering 24 hours of turbine operation.

$$R_{tm} = \frac{Q_{dt} \times 36 \times 24}{10^3} \tag{7.5}$$

R_{td}= Minimum desired release (Mm^3),

p_k= Peaking hours (h),

R_{tm} = Maximum possible release (Mm^3)

5) Actual Release at any time period is decided based on the available storage prior to that time period, inflow in that time period and target reservoir elevation at that time period. This is achieved through the following steps.

6) Actual turbine release and spill are calculated based on the constraints of

a. Proposed desired reservoir elevation (maximum) at that time period

$$R_{ta} = S_t + I_t - K_{El} - E_t - R_m \tag{7.6}$$

$$S_p = S_t + I_t - K_{El} - R_{tm} - E_t - R_m \tag{7.7}$$

where, R_{ta} = available release (Mm^3),

S_t = storage of the reservoir at beginning of time period t (Mm^3),

I_t = inflow (Mm^3)

K_{El} = capacity of reservoir (Mm^3),

E_t = evaporation (Mm^3),

R_m = minimum mandatory release provided (Mm^3).

b. Minimum drawdown level

$$R_{ta} = S_t + I_t - S_d - E_t - R_m \qquad 7.8$$

where, S_d= dead storage *(Mm^3)*

7) Storage at the end of the time period t is calculated based on the release computed in step-6.

$$S_{t+1} = S_t + I_t - R_{ta} - S_p - E_t - R_m \qquad 7.9$$

where, S_{t+1} = storage at end of the time period *t* (Mm^3)

8) New reservoir elevation El_{nt} *(m)* is calculated using storage-Elevation relationship

9) Net head is then calculated taking the average of initial elevation El_t at beginning of time period t and the new elevation El_{nt} at end of the time period t, and the entire calculation from step 1 is repeated to obtain the actual discharge by iteration (convergence threshold of 0.0001 m^3/s)

10) Water balance is also checked in all these computation to ensure computational accuracy.

11) Total downstream flow, TDF (Mm^3) is computed as;

$$TDF = S_t + I_t - S_d - E_t + S_p \qquad 7.10$$

12) After obtaining the actual discharge in step 9, the hours of operation of the turbine, power generated through the turbine *Po* in (*MW*), Total power generated per hour *Poh* in (*kWh*) and total downstream flow TDF (*Mm^3)* is calculated.

7.3 RESULTS AND DISCUSSION

RSM developed has been applied to the Lower Subansiri HE project. Simulation carried out on 10 daily bases has shown the following:

1. So far the total flow volume of 10 days is concerned, only minor variation from existing normal flow condition will occur due to presence of dam. Fig 7.1 shows the Inflow series and Total Downstream Flow (TDF) series for 26 years, and Fig 7.2 shows the quantity of power produced during that period.

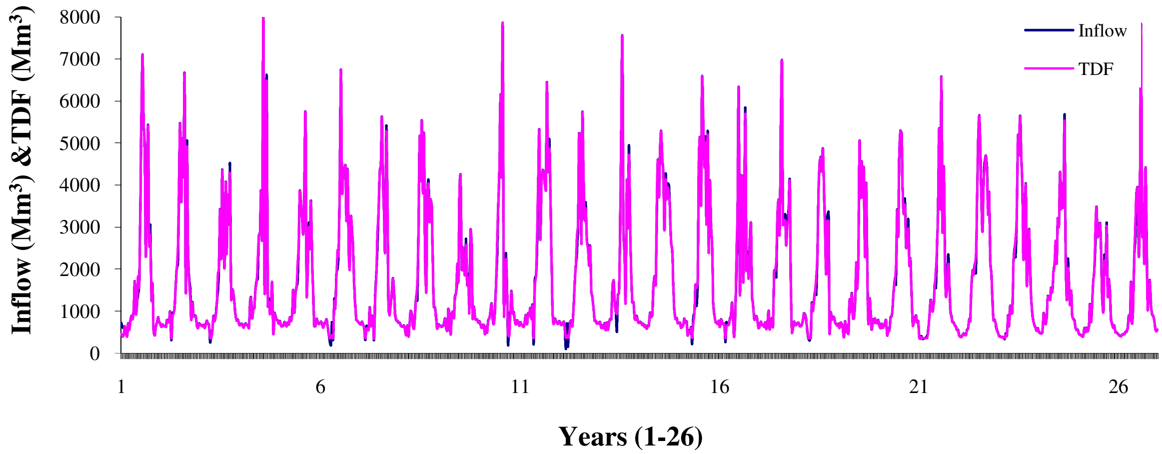

Fig 7.1 Plot of Inflow and TFD for 26 years

2. A close view of this series is shown for first years in Fig 7.2. This output of the developed model has clearly revealed that total ten daily Inflows in ten days and the Total Downstream Flow (TDF) after construction of dam are of same order. Visible variation has been observed only in the month of May-June, as the reservoir is drawn down during that period to keep sufficient space for accommodating high discharge during monsoon period, which will also provide opportunity of moderating high flood of small duration (smaller than 10 days).

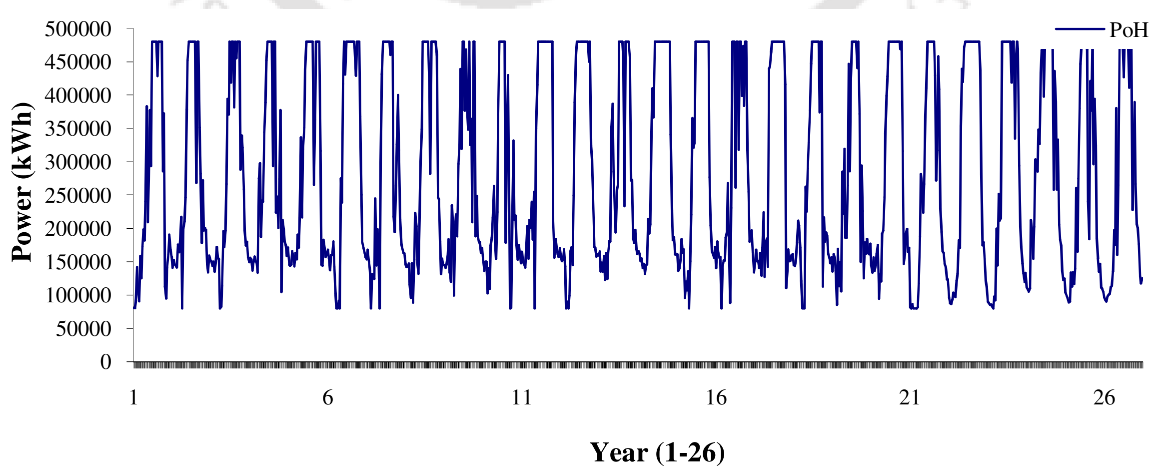

Fig 7.2 Plot of power production for 26 years

3. Fig 7.3 shows close view of pattern of total power production in two different years. It can be observed from these figures that the power hour is very high in the wet season. Power production remains high from the month of May to October. It reaches its peak in the month of June and July and more or less it follows the similar pattern as of inflow. Power production is less in the dry season but is sufficient to generate full capacity (2000MW) for a minimum of 4 hours of peeking hour.

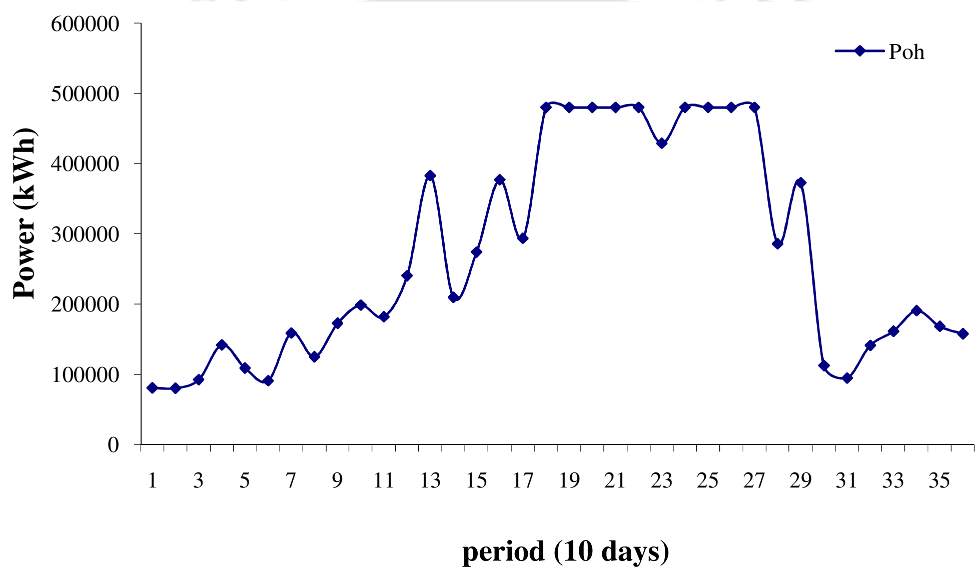

Fig 7.3 Close view of power production for 1st year

4. However, though total flow volume in ten days remains more or less same before and after construction of dam, rate of flow in the downstream varies significantly. Fig 7.4, 7.5, 7.6 and 7.7 shows the flow situation downstream of the dam along with the time of such flow. Average natural flow condition is also plotted to have a comparison. Fig 7.4 through Fig 7.7 clearly shows the difference in flow rate between the present situation and the situation after dam. The difference in flow rate is much more significant in the lean period, where the maximum flow rate become 2500 m^3/s and minimum flow rate become 6 m^3/s, while the average flow rate in the lean period in natural situation is about

500 m^3/s. Fig 7.6 shows the variation of flow duration for the maximum flow rate that produces power up to capacity of 2000MW.

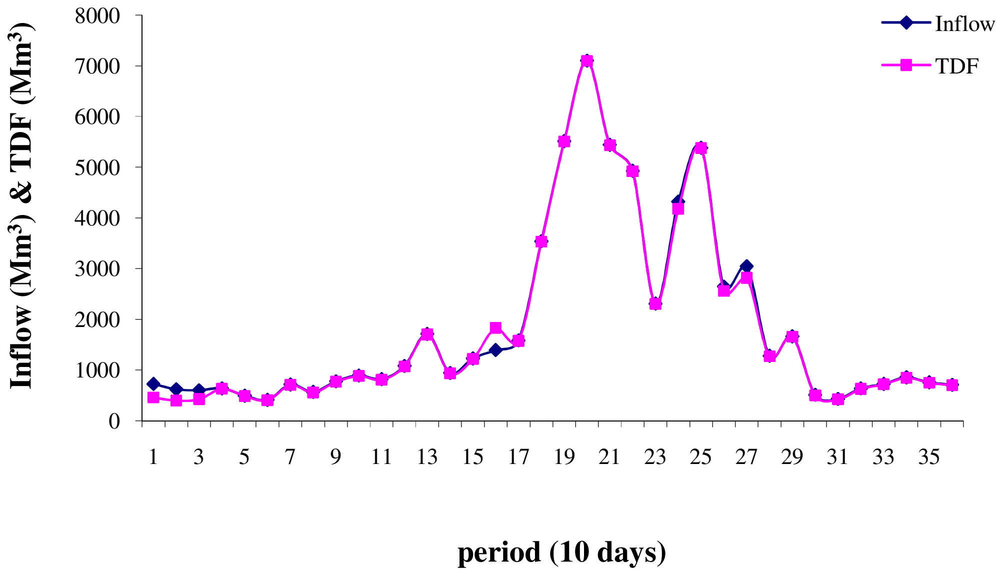

Fig 7.4 Close view of inflow and TDF for 1st year

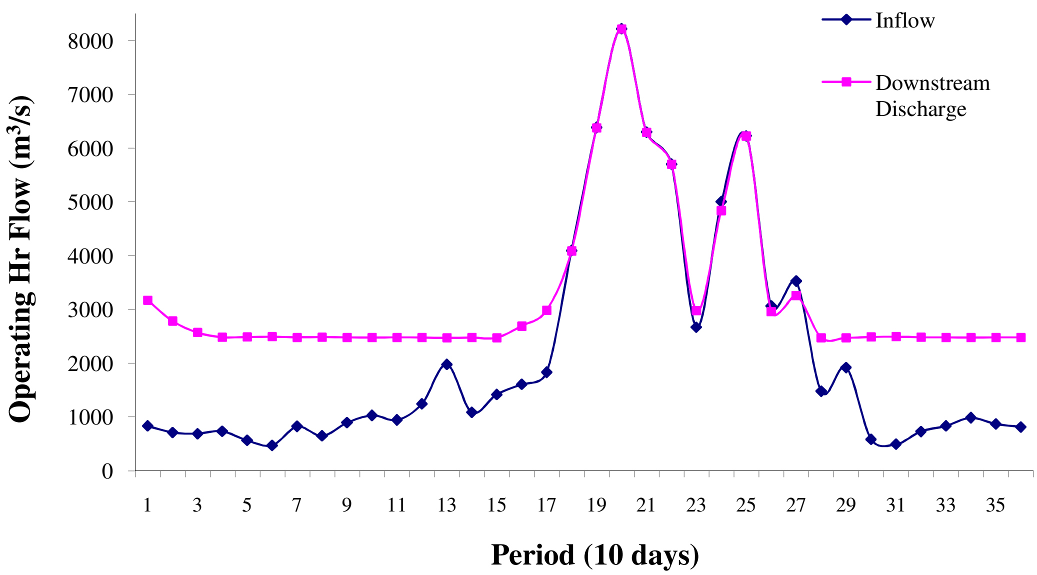

Fig 7.5 Plot of rate of inflow and rate of TDF for 1st year

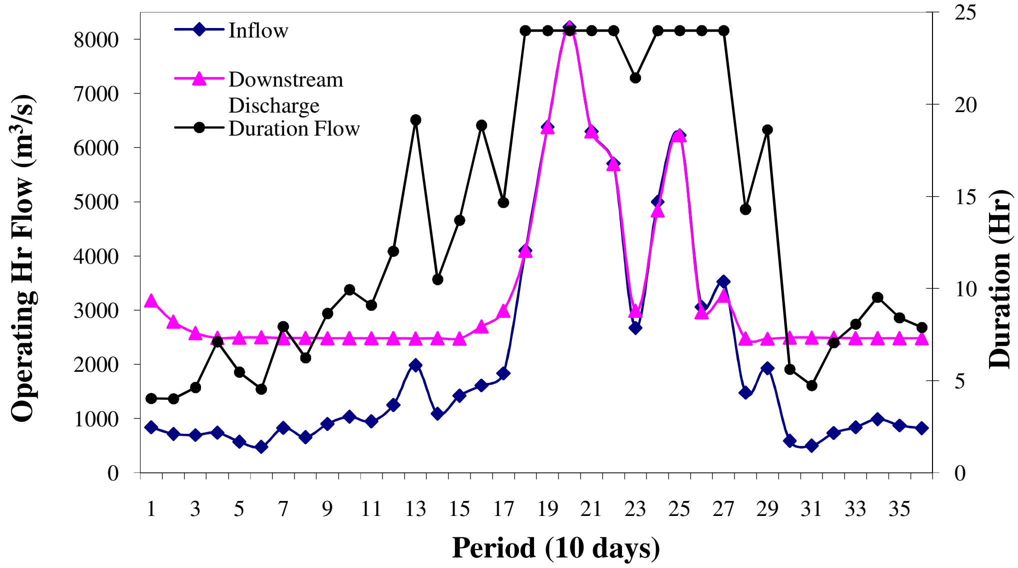

Fig 7.6 Plot of rate of inflow, rate of TDF and duration of TDF for 1st year

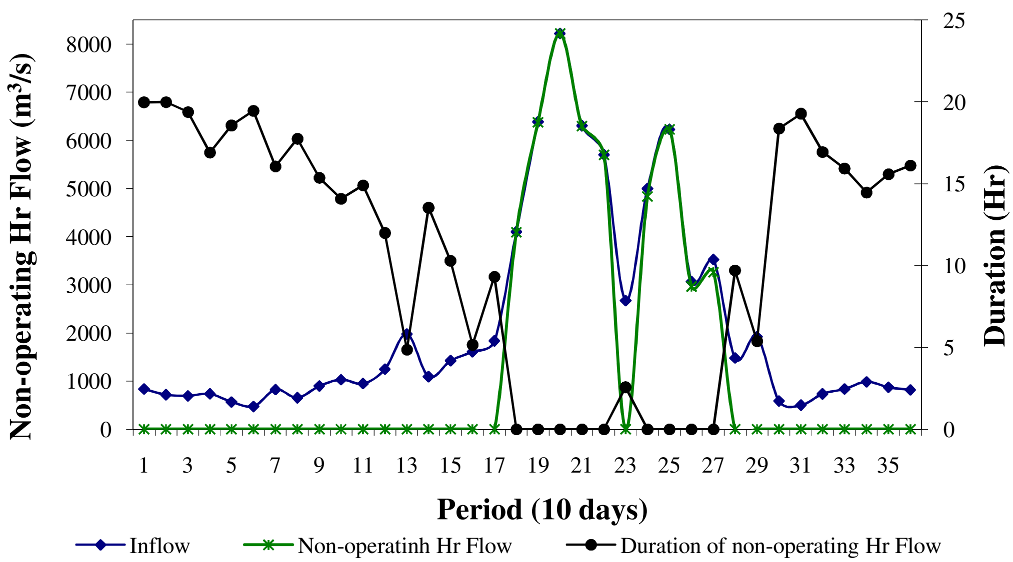

Fig 7.7 Plot of rate of inflow, non-operating Hr Flow and duration of Flow for 1st year

Fig 7.8 represents the variation of storage and corresponding change in elevation at the end of time t, from the Fig 7.8 it is clear that the curve of reservoir storage change and elevation change are of similar nature.

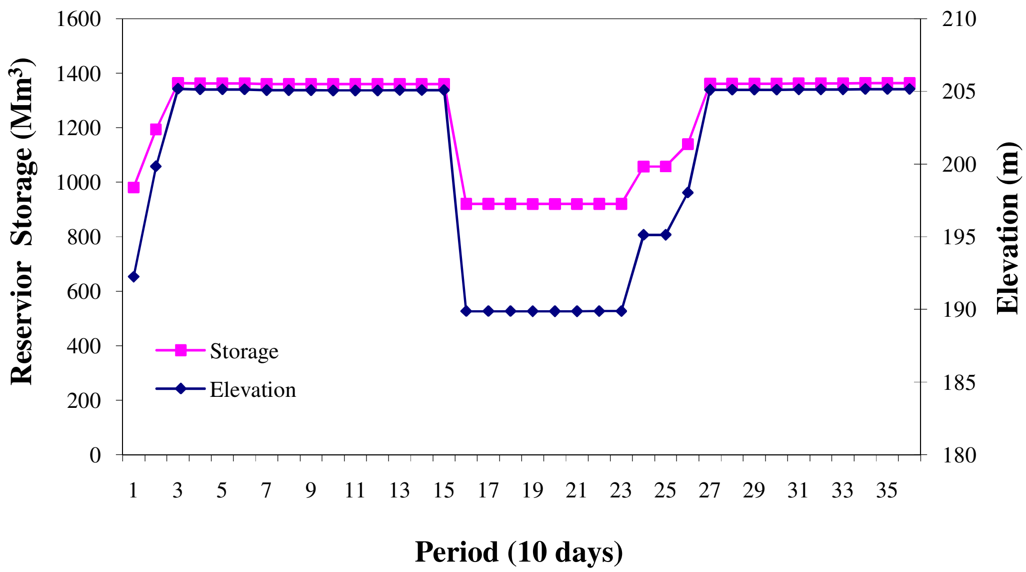

Fig 7.8 Plot of Reservoir Storage and corresponding elevation 1st year

Simulation result has shown that the diurnal variation is more significant for the lean period as the flow discharge will be in the order of 2500 m^3/s for the peaking hour with only 6 m^3/s of discharge in the remaining period. Where as it is important to note that the average flow rate during lean period is in the order of 500 m^3/s. This diurnal variation may influence the river downstream leading many impacts. To have an idea about influence of changing flow scenario and its expected impact on downstream water quality a study is conducted.

Minimization of diurnal variation of flow can be a solution to the many above problems downstream. From environmental point of view, the natural flow condition prevailing in the stream before construction of dam can be regarded as the most preferred flow condition. Therefore, an effort should be made to have a flow condition as close as possible to the natural flow, i.e. pre-dam flow condition. This study attempts to reduce the diurnal variation of the flow through different structural and non structural means. Efficiency of different proposed techniques has been assessed through simulation study. It is envisaged that by minimizing such flow variation in the river, it will be possible to minimize the ecological and environmental disturbances to a reasonable extent. Some measures to reduce diurnal variation downstream are proposed in the following sections.

7.3.1 Proposed Measures for Minimizing Diurnal Variation

Considering the constraints of practical feasibility and requirement of meeting power demand, the following approaches have been developed for minimizing diurnal variation of flow.

Structural measures: Regulating-pond at downstream

Non-Structural measures: Regulated turbine operation

a) Structural Measures: Regulating-Pond at Downstream

Several measures for minimizing variation of flow downstream of the dam have been thought about and simulation has been carried out to visualize the effect of such measures, Structural measure is one of the measures thought for the minimization of diurnal variations. A new idea of introducing a small capacity pond downstream of the reservoir was investigated to explore possibility of minimizing diurnal variation and to analyze its performance and practical feasibility. In this approach, we propose construction of a regulating pond downstream of the turbine for regulating high discharge released from the turbine during operational hours. The size of this pond will depend on the installation capacity of the project and amount of regulation envisaged. Analysis of the terrain has also shown that it will be possible to create such storage just at downstream of the dam without raising the tail water level, i.e. without reducing the net head. Simulation study has shown that diurnal variation of flow could have been significantly minimized by creating a downstream storage of 36 Mm^3. Fig 7.9 shows the curves showing the ranges within which the downstream will vary if a 5m high barrier covering the entire width at 4Km downstream of the dam is placed.

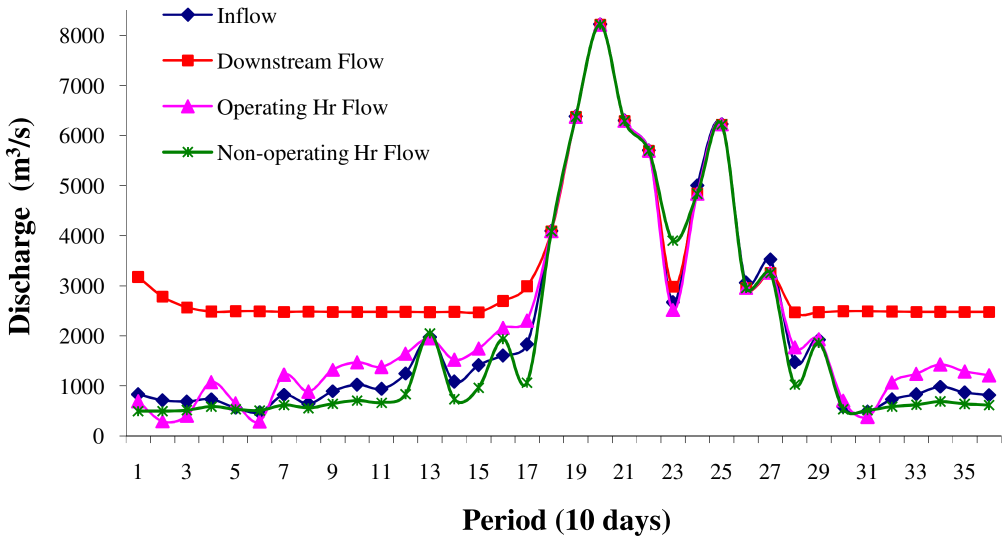

Fig 7.9 Comparisons of inflow, downstream flow, operating hour and non-operating hour flow

Fig 7.10 presents the comparisons of non-operational hour flow i.e. the flow downstream when the turbine is not in operation with natural inflow. The plot also shows the duration of non-operational hour flow downstream. It depicts that non-operating hour flow is following the same patter as the natural inflow. From the Fig 7.10 it seems clear that the duration of operational hour flow in a day in lean season is high which means in a day flow downstream is quite similar to natural flow condition that in fact is good to sustain the environmental equilibrium. This condition is favorable for downstream river biota to adapt harmoniously with natural environment and to maintain the life cycle. Fig 7.11 is the plot of operating hour flow, natural inflow and the duration of flow. The operating hour is little high as compared to inflow but overall it follows the same trend. Hence implementation of the structural measure ensures the more or less similar flow both in operating hour and non-operating hours without compromise of the power production.

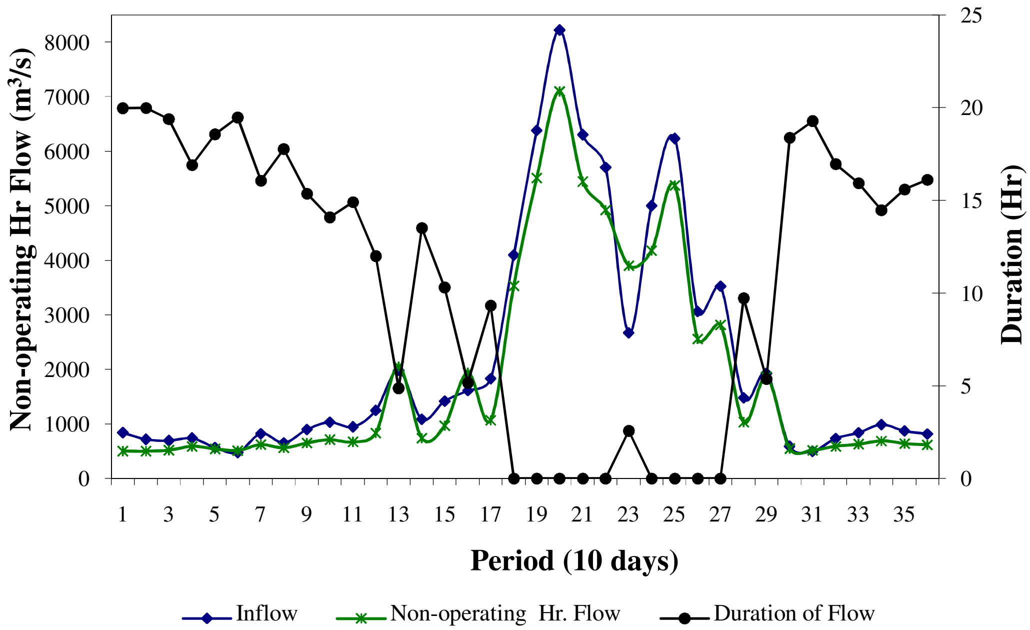

Fig 7.10 Plot of inflow, non-operating hour flow and duration of flow.

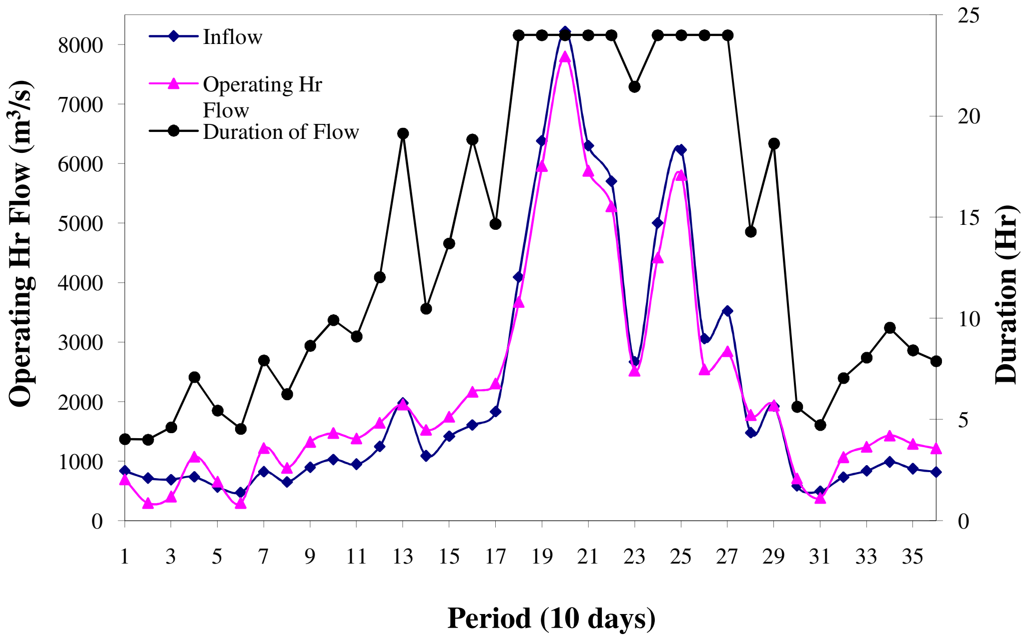

Fig.7.11 Plot of inflow, operating hour flow and duration of flow.

Though the results were quite exciting, this option has been found practically difficult due to following facts:

i). Width of the stream is about 4Km at that section with wide flat valley, which will require marginal embankment up to the foothill portion. Marginal embankment will obstruct flow of three streams on left and one stream on right into the Subansiri River. Obstruction of stream may cause flooding upstream of these streams in the flood period.

ii). As the water level during flood time is high a huge staging of about 4Km length and of about 30 m height will be required for gate operation. Apart from the constraint of cost, possibility of damage to such structure during flood time cannot be ruled out.

iii). Reservoir will continue to release sediment through the orifice spillway of the dam. Though initially the sediment load will be reduced, considering the sediment load of the stream, it is expected that the flow released through the spillway during flood period will still contain enough sediment, which will get deposited in this downstream storage space, as velocity of flow will drop significantly. This will reduce the capacity of such storage within a short period. As such in long run function of this small storage may not be effective.

b) Non-Structural Measures: Regulated Turbine Operation

However, though total flow volume in ten days remains more or less same before and after construction of dam, rate of flow in the downstream varies significantly.

Non-structural measures: the number of turbines to be operated in different time period is regulated as per the following two options.

i) Operating one turbine continuously at full capacity and operating rest of the turbines simultaneously for maximum possible duration, so that effort can be made to utilize the available water in the reservoir for meeting peak power demand. This approach is proposed basically to minimize duration of occurrence of high flow discharge at downstream and to create a near natural flow condition in the downstream for a longer duration.

ii) Operating one turbine continuously for 24 hours and increasing the number of turbines one by one, so that a turbine once put into operation can be run for maximum possible hours subject to water availability. By this approach high rate of flow at downstream due to simultaneous operation of all turbines as proposed in 'option a' can be minimized to a great extent, of course with the compromise of peaking power.

Overall performances of these options are analyzed through simulation study and presented below.

Non-structural measure-I: Operating One Turbine Continuously and Operating Rest of the Turbines Simultaneously **:** Option of providing minimum flow of around 300 m^3/s in the lean period to produce 250MW power continuously by running one turbine for the entire day and to produce 1750MW with the remaining water for the possible period. This will ensure minimum flow of $300 m^3/s$ throughout the day in the lean period with maximum flow of around $2500 m^3/s$ for the peaking duration, which will not be less than 2 hours per day even in the lean period. Fig 7.12 shows the plot of maximum, minimum downstream flow and natural

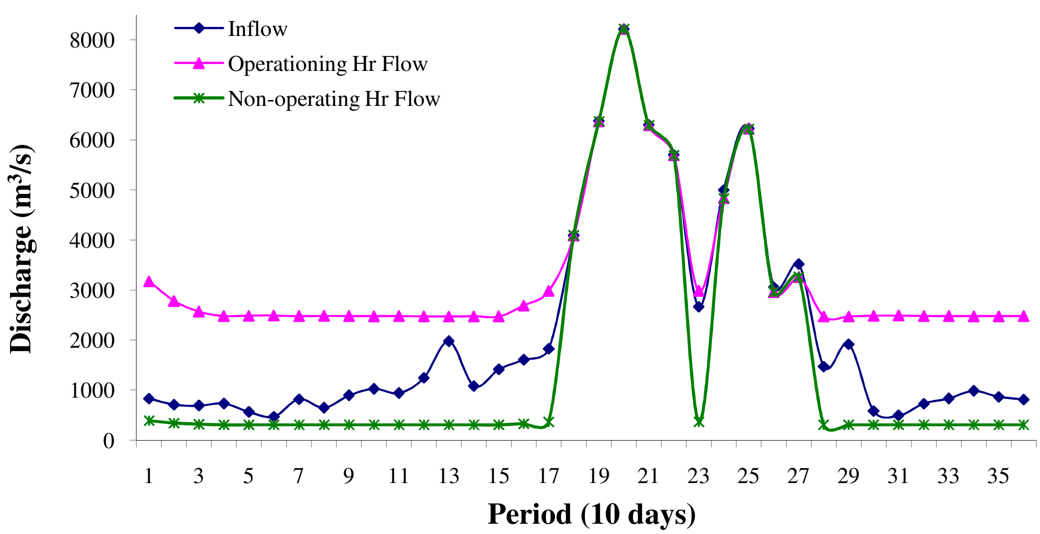

Fig 7.12 Comparison of inflow, operating hour flow and non-operating hour flow

inflow rate with one turbine running continuously. Fig 7.13 shows the plot of minimum downstream flow, its duration in a day and natural inflow rate with one turbine running continuously. Fig 7.14 shows the plot of Maximum downstream flow, its duration in a day and natural inflow rate with one turbine running continuously.

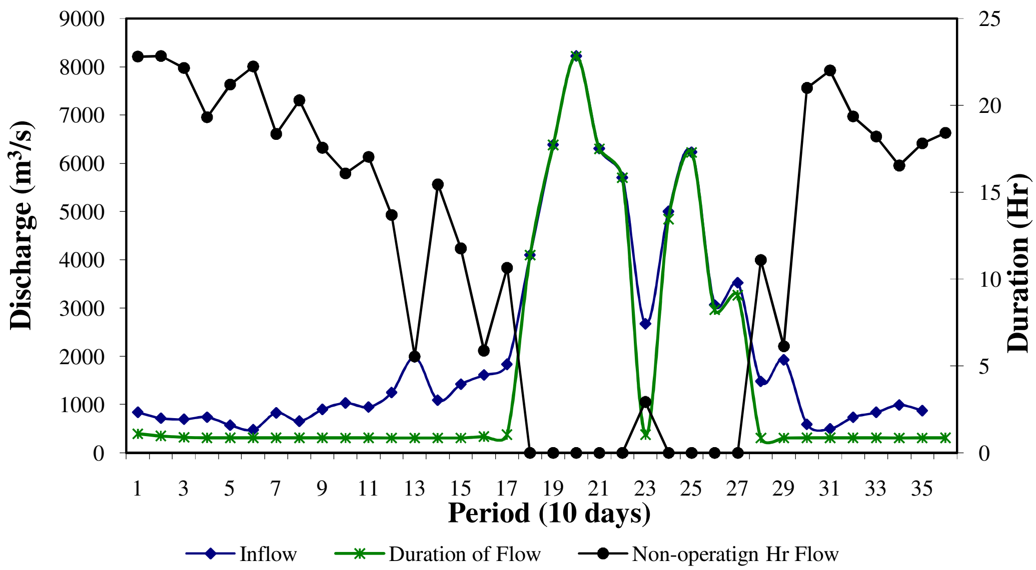

Fig 7.13 Plot of inflow, non-operating hour flow and duration of flow

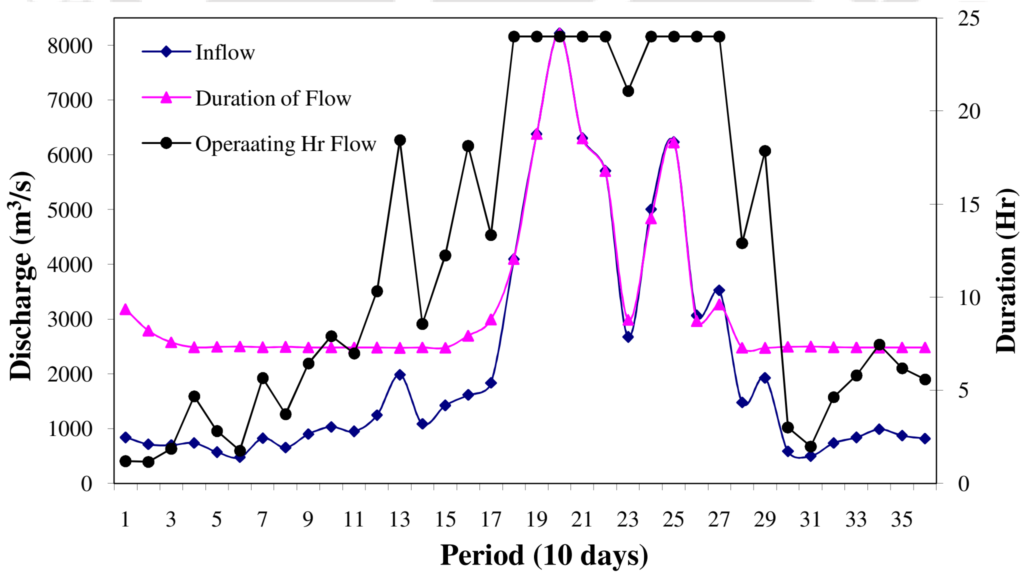

Fig 7.14 Plot of inflow, operating hour flow and duration of flow

<u>Non-structural measure-II:</u> Operating One Turbine Continuously and Increasing the Number of Turbines One by One: Another option of utilizing the available water by running one turbine continuously and then increasing the number of turbine one by one for maximum possible hours of operation for each of the added turbine. This will restrict maximum rate of flow, off-course with a compromise with peaking power. Fig 7.15 shows the maximum and minimum rate of flow through turbines along with the plot of natural inflow.

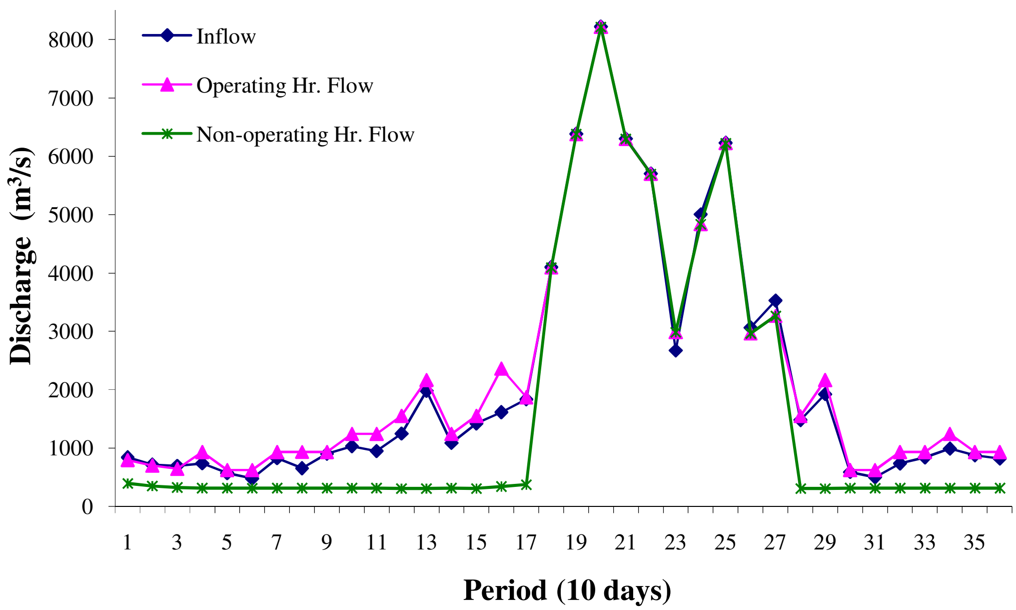

Fig 7.15 Comparisons of inflow, operating hour flow and non-operating hour flow

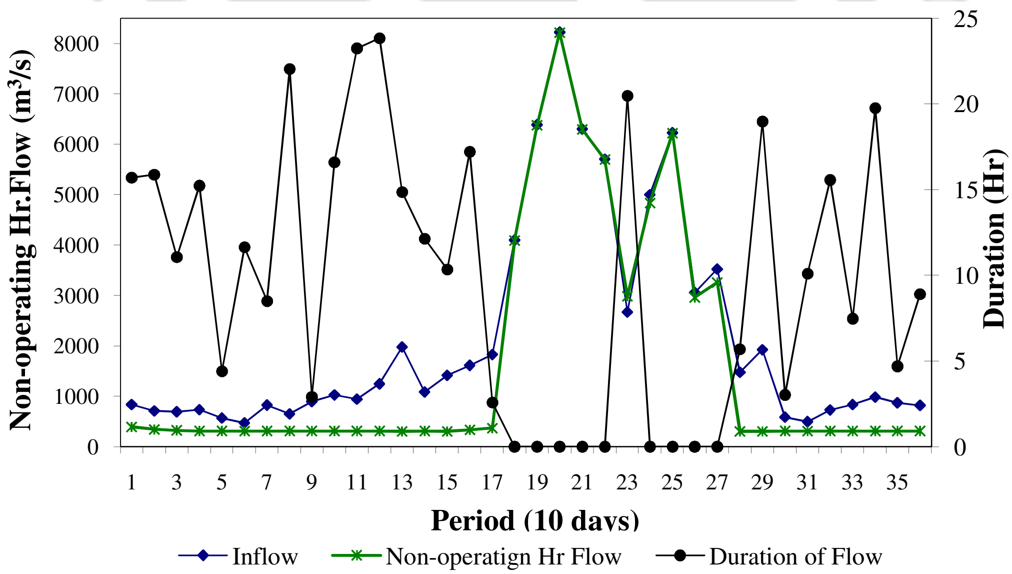

Fig 7.16 Plot of inflow, non-operating hour flow and duration of inflow

Fig 7.16 shows the inflow, non-operating hour flow and the duration of flow. Fig 7.17 shows the inflow, operating hour flow and the duration of flow.

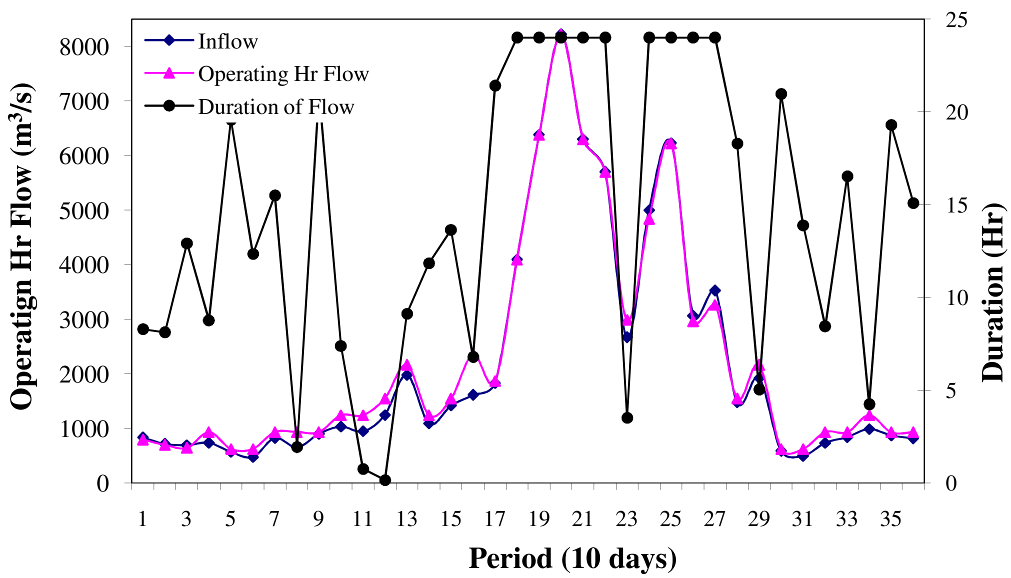

Fig 7.17 Plot of inflow, operating hour flow and duration of flow

7.4 Comparisons of Proposed Measures

A reservoir simulation study has revealed that with standard operating policy without the mitigation measures, the downstream will be subjected to a diurnal variation ranging from 6m^3/s to 2500m^3/s in lean period and average annual power production will be 10169 MU (1 MU=106 kW-h) with minimum peaking hours of 4 hours per day. With the adoption of a structural measure, the range of diurnal variation of flow will be reduced to 500 - 2500m3/s in lean period. It will be possible to achieve this without compromising the average annual power production or minimum peaking hour per day. Adoption of non-structural measures has also shown encouraging results: (i) By running one turbine continuously and producing peaking power with the remaining water, the diurnal variation will range from 314 to 3013m^3/s in lean period and annual average power will be 9153.346MU, while the minimum peaking hour will be reduced to 2 hours. (iii) With the second proposed modified operating policy i.e. by adding turbine one by one, the diurnal variation will range from 310m^3/s to 1500m^3/s in lean period. Average annual power will be 8505.785MU, but in a day minimum peaking hour, for which the plant will produce 2000 MW of power will be reduced to 0 hr in lean period. A comparative performance of these mitigation measures is presented in the Table 7.1. Comparison has been drawn on the basis of seven performance criteria: average annual power production, minimum peaking hour per day (producing 2000 MW), minimum downstream flow, maximum duration of minimum downstream flow, probability of failure to meet the 4 hours peaking requirement, maximum deficit during peaking hour and percentage of maximum power deficit during the peaking hour. Table 7.1 shows clearly that the proposed structural measure can be considered the best mitigation measure, as minimum downstream flow of 417 m^3/s can be provided without compromising power production. Adoption of this measure will require a favorable site condition and additional initial investment. Out of the two operational measures, Non-structural measure -I is better and can

Table 7.1 Performance criterion for different measures

Performance Criterion	SOP	Structural measure	Non-structural measure-I	Non structural measure-II
Average Annual Power Production (MU)	10169	10169	9153.346	8505.785
Minimum Peaking Hour per day	4	4	1.14	0.00
Minimum Downstream Flow (m^3/s)	6.00	417.00	314.00	310.00
Probability (%) of failure to meet the 4 hours peaking requirements	0	0	12.18	69.23
Maximum Power deficit during peaking hours	0	0	0	6968.71
% maximum power deficit during peaking hours	0	0	0	6.52

be adopted wherever practical implementation of structural measure is not possible. This method will provide minimum streamflow 314 m^3/s, but with 12.18 % probability of not being able to meet the minimum peaking power demand of 4 hours. However, even under these conditions the project will be able to provide peaking power demand for at least 1.14 hours. Non-structural measure–II cannot be recommended, as it will not be possible to meet the peaking power demand for 69.23 % of the time. It is also important to note that for some of the unsuccessful cases the project will not be able to generate its full installed capacity i.e. 2000 MW for even an hour (Table 7.1). Total annual power generation will also be reduced to 8505.785 MU.

7.5 Conclusion

A reservoir simulation model has been developed to investigate the augmented flow scenario downstream of a hydroelectric project, and the necessary corrective measures to minimize downstream environmental impacts have been suggested. The model has been applied to the Lower Subansiri Hydroelectric Project in Assam, India. The simulation study shows that with the proposed power production schedule i.e. with peaking hour of minimum 4 hours, the downstream flow will be changed with a diurnal variation between 6 to 2500m^3/s in the lean period as compared to the natural flow, which is in order of 500m^3/s. Such diurnal variation in the streamflow will have adverse ecological effects. During the flood period, diurnal variation induced by the reservoir operation is not that significant and thus will not create any adverse effect. The scope of minimizing diurnal variation through structural and nonstructural mitigation measures have been investigated through simulation study. The reduction in diurnal flow variation can be effected by introducing a regulating (balancing) pond downstream of the dam (structural measure); the non-structural measures try to achieve minimum diurnal variation by modifying the operating schedule. Performances of these mitigation measures have been compared on the basis of seven different performance criteria. Comparisons have revealed that structural measures provide the best solution. As an alternative, by changing the operational schedule of the hydroelectric power production (non-structural measure-I) will also provide notable improvements over the baseline standard operation scenario.

Chapter 8

Reservoir Operation Model Using Deterministic Dynamic Programming

8.1 Introduction

Generally hydro power projects are designed to obtain maximum benefit through power production. Storing large volume of water and then releasing it later for the power production becomes the system requirement. When these hydro power projects are operated as run-off-river projects, to meet the peaking power demand becomes the primary objective of the project. Operation of such projects induces significant diurnal variations downstream of the dam affecting downstream environment and leading to various losses in due course of time. More the water stored more is the power generation, but more is the diurnal variation, which in turn inflict various losses. At this point, it becomes very much important to know, which combination of storage and release will draw maximum net benefit, i.e, the benefit from power generation after deducting losses due to flow variation induced by turbine operation. Optimization technique can provide a solution in such situation. To obtain solution of such problem dynamic programming is an efficient tool. Dynamic programming is an approach used to get a solution of multistage problems. In multistage problems, decision problems are divided into a sequence of separate but interrelated single-decision sub-problems. The solution of the problem is carried out in stage- by- stage manner till the final result is obtained. Thus the problem whose solution is desired, needs to be decomposed into subproblems and each is designated as a stage. The decomposition can be done with respect to time or space. The stage is characterized by a state which is expressed by numerical values of sate variables. Transition of one state to other is governed by the particular decision or course of action, which is represented as decision variable. Change of the state is described by the state transformation function. Transformation is possible only if certain rules, i.e. constraints of the system are satisfied, at this juncture both state and decision variables take the values of predefined domain. Most of the reservoir operation problems are multi decision problems, for example, deciding release at different time period. DP is more suitable approach to solve such kind of problems. Moreover DP has capability to handle nonlinear objective functions and nonlinear constraints hence widely applied in reservoir operation studies. If DP is applied to determine reservoir releases, the state variable is storage, the decision variable is release and the stage is represented by time period. Past studies (Ahmed and Sarma 2007) shows that the deterministic DP requires long series of stream flow, it may be either historical or synthetically generated. 100 years of synthetic series averaged over ten daily time step is used in the deterministic DP model of the present study. As the deterministic DP model uses a specific streamflow series, it can't be designated as general optimal operating policy (GOOP). Therefore to derive general optimal operating policy (GOOP) applicable in practical field, multiple linear regressions called DPR from the results of DP model is attempted. C-programming has been used to develop the computer programme required for optimization and simulation study.

8.2 Model Formulation Using Deterministic DP

8.2.1 Model Formulation

A backward moving discrete dynamic programming has been formulated for LSHE project. The objective function considered in this study is maximization of net benefit, the detail of the problem formulation is given in chapter 4 and chapter 5. The problem is decomposed in different stages with respect to time period i.e. ten daily periods. Each stage is characterized by state variable that is reservoir storage in this problem. The reservoir release is considered as decision variable here. The deterministic DP model has been formulated to develop ten daily operating policies.

Recursive Equation:

Objective Function

The objective function for the deterministic dynamic programming is formulated as follows.

$$Maximize\ f = \sum_{t=1}^{T}\left(P_{bit} - (L_{fat} + L_{fpt})\right) \qquad 8.1$$

where,

P_{bit} = profit from power production during time period *t;*

L_{fat} =loss of agriculture at downstream due to water scarcity at time period *t*;

L_{fpt}= loss of fish production at downstream due to water scarcity at time period *t*;

T = 3600; 36 stages per year for 100 years.

The major losses that affect the livelihood of the downstream community directly are considered for assessing the losses. These losses are loss of agriculture and loss of fish production due to diurnal variations, detail of these losses and problem formulation are discussed in chapter 4 and chapter 5.

The expanded form of equation 8.1 is written in equation 8.2 to 8.6

Maximize

$$f = \sum_{t=1}^{3600}\left[\left(\frac{1}{2}\eta g Q_{dt}(H_n + H_{nn})R_p H_r\right) - \left(\left(289870^{-0.0006Q_{nt}}\right) + \left(w_t \times \left(\frac{250 - Q_{nt}}{250}\right) \times L_{fft} \times R_f\right)\right)\right]$$

8.2

$$Q_{dt} = \frac{R_t \times 10^6}{H_r \times 3600} \qquad 8.3$$

$$Q_{nt} = \frac{(S_t + I_t - R_t - E_t - K_{El}) \times 10^6}{(240 - H_r) \times 3600} \quad 8.4$$

$$H_n = El_t - El_{tail} - h_f \quad 8.5$$

$$H_{nn} = El_{nt} - El_{tail} - h_f \quad 8.6$$

The recursive equation for the above function at any time period t can be written as

$$f_t^{\,n}(S_t) = \underset{S_t \in \varphi_t}{maximum}[Z_t + f_{t+1}^{\,n+1}(S_{t+1})] \quad 8.7$$

$$Z_t = \left(P_{bi} - (L_{fat} + L_{fpt})\right) \quad \text{where,} \quad \text{for } Z_t > 0; \quad 8.8$$

t = index of time period (10 days);

H_r= Duration of turbine operation (hour);

η = the combined efficiency of turbine and generator in percent;

g = gravitational acceleration (9.81) m/s^2;

Q_{dt} = discharge passing through turbines m^3/s for time t;

Q_{nt} =discharge in non-operating hours m^3/s for time t;

L_{ff} = fish production (kg) for time t;

w_t= weightage given to fish production;

$R_{f=}$ cost of fish per kg (Rs);

H_n= Net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at beginning of time t (m);

H_{nn} = Net hydraulic head (difference of reservoir elevation at time t and normal tailrace level) at end of time t (m);

S_t = reservoir storage (a state variable) at the beginning of time period t (Mm^3);

I_t = inflow at time t (Mm^3);

E_t = evaporation at time t (Mm^3);

R_t = release at time t (Mm^3);

K_{El} = Storage capacity of reservoir at time t (Mm^3);

φ_t = discrete set of characteristic storage volumes considered at the beginning of time period t;

n = total number of time periods remaining including the current period before;

El_t =elevation of reservoir at the beginning of time t (m);

El_{nt} = elevation of reservoir at the end of time t (m);

El_{tail} = elevation of normal tail race water (m);

h_f = head loss due to friction (m) corresponding to El_t and $El_{n;}$

The above recursive equation is solved subject to the constraints given below, details of mathematical formulation of each have been discussed in chapter 4.

<u>Continuity Constraint</u>

$$S_{t+1} = S_t + I_t - R_t - E_t - R_m \qquad 8.9$$

where, R_m = minimum downstream release = 6 ×10×24×3600/10^6 which the project proposes to release primarily to meet the water requirement of river reach between dam and the tail race confluence.

<u>Reservoir Storage Constraint</u>

$$S_d \leq S_{t+1} \leq S_{t\max} \qquad 8.10$$

where, S_d dead storage (720 Mm^3), S_{t+1} is storage of the reservoir at the end of time t, S_{tmax} is maximum storage of reservoir (1365 Mm^3).

<u>Release constrain</u>

$$R_{t\min} \leq R_t \leq R_{t\max} \qquad 8.11$$

$$R_{t\min} = \max[0, (S_t + I_t - E_t - K_{El} - R_m)] \qquad 8.12$$

$$R_{t\max} = S_t + I_t - E_t - S_d - R_m \qquad 8.13$$

where, R_{tmin} = minimum release in time t based on reservoir storage constraint, R_{tmax} is maximum release made at time *t*, K_{El} is capacity of reservoir at time *t*, R_t is available release at time *t*

Environmental Constrain

$$R_t \geq R_{tdm} \tag{8.14}$$

where, R_{tdm} is the minimum mandatory flow that policy maker may decide to provide at downstream to maintain near natural flow. 250 m^3/s is considered for the present study to conduct the case study.

8.3 Deterministic Dynamic Programming Model Application

8.3.1 Discretization of Storage

The LSHE project is proposed to be operated from storage volume of 720 Mm^3 (Maximum Draw Down Level) to 1365 Mm^3 (Full Reservoir Level). The reservoir capacity will be kept different for different time period. The level of reservoir will be lowered down in the wet period in order to accommodate the incoming flood of short duration, while it will be kept high in lean season hence to achieve maximum power production. Therefore conservative storage of the reservoir is 645 Mm^3. The total conservative storage is discretize in 44 characteristic storages of 15 Mm^3 each.

8.3.2 Input Data

The data used for developing the deterministic dynamic programming model are:

(1) 100 years of synthetic ten daily streamflow (i.e. T =3600).

(2) Ten daily reservoir capacity.

(3) Ten daily evaporation rate.

(4) Cost of power production per unit (kWh).

(5) Cost of agricultural product per kilogram.

(6) Cost of fish production per kilogram.

Ten daily evaporation is computed as the product of ten daily mean reservoir area and ten daily evaporation rates.

8.3.3 Model Results

The deterministic dynamic programming model with 44 discrete storage has been solved for set of input data mentioned above. The solution of the deterministic dynamic programming gives the optimal releases against the initial storages and inflows into the reservoir for 3600 ten daily periods. Therefore a large number of patterns consisting of initial storage, inflow and optimal release are obtained from the solution of deterministic dynamic programming. Table 8.1 shows the number of characteristic storages, discretization steps, and the number of patterns consisting of initial storage, inflow and optimal release.

Table 8.1 Number of characteristic storage, decretization and pattern

Number of characteristic storage	Discretization step (Mm^3)	Number of Patterns obtained
44	15	158400

The output patterns obtained from the deterministic dynamic programming result gives optimal solution only for the streamflow series considered in the development of it, which can't be used as general operating policy. Hence general optimal operating policy (GOOP) must be derived. To derive GOOP the multiple linear regression approach using the patterns from the deterministic DP has been tried in the present study. The policy derived using multiple linear regression rule is called DPR. The details of the DPR are presented below.

8.4 Multiple Linear Regression Model

Multiple regression is one of the common approach to derive general reservoir operation policy. This approach has been used by many researchers in the past viz. Young (1967), Bhaskar and Whitlach (1980) and Karamouz and Houck (1982), Raman and Chandramouli (1996), Ahmed and Sarma (2007). In the present study the linear and different non-linear expressions have been tried and optimal release is decided using linear function of the inflow and initial storage of the reservoir during time period t, as this expression is simple and the mean relative error (MRE) found using this expression is less while the maximum deviation of absolute error is accepted. Different forms of the expressions tried in the study are presented below in the Table 8.1. It can be seen from the table that maximum of the absolute value of the deviation of the data from the model, MRE and the type of the model, are such criterions on basis of which selection of model is carried out. The selected expression for the optimal release is presented in equation 8.15

Table 8.2 Different form of expressions tried for study

Expressions	MRE value
$R_t = a_1 I_t + a_2 S_t + a_3$	41.2256
$R_t = a_1 \exp(-I_t) + a_2 \exp(-S_t) + a_3$	111.27
$R_t = a_1 \sin(I_t) + a_2 S_t + a_3$	112.134
$R_t = a_1 I_t + a_2 S_t + a_3 I_t S_t + a_4 I_t^2 + a_5 S_t^2 + a_6$	22.1364

$$R_t = a_1 I_t + a_2 S_t + a_3 \qquad 8.15$$

where, a_1, a_2 and a_3 are the coefficients of the regression equation of general operating policy.

The resultant patterns obtained from the Deterministic DP are regressed using least square fitting. The linear regression for the patterns obtained from deterministic DP results is carried out. The DPR1 and DPR2 are developed for two cases GOOP1 and GOOP2. The GOOP1 means the GOOP is developed using the constraint of minimum downstream environmental release as 250m^3/s in non-operating hours while GOOP2 means the GOOP developed with only 6m^3/s discharge in non-operating hours which is negligible discharge but decided to provide by the project management, as minimum downstream environment release. The coefficients of the regression models are presented here;

Table 8.3 Coefficient of DPR1and DPR2

Type of model	Coefficients of the model		
	a_1	a_2	a_3
DPR1	0.5595	0.4028	-341.972
DPR2	0.4924	0.1954	176.9844

8.5 Results and Discussion

8.5.1 Case –I (DPR1)

The GOOP1 is developed for the LSHE project in the present study. The "GOOP1" developed for the reservoir operation using multiple regressions (DPR1) is evaluated through "SOP1" developed using reservoir simulation model (RSM) using 26 years streamflow series. Detail of the RSM is presented in chapter 7. The simulation is started on first ten day period of month January and with initial storage 1365 Mm^3 (FRL) and the final period of simulation is third ten day period of December. The final output of the GOOP1 and their comparison with SOP1 is presented through the Fig 8.1 to Fig. 8.6 below. The SOP1 means the SOP developed using the constraint of minimum downstream environmental release as 250m^3/s in non-operating hours same as, used for the development of GOOP1. The annual net benefit obtained from the GOOP1, SOP1 is shown in Fig 8.1; it becomes clear from the figure that annual benefit obtained by the GOOP1 is relatively higher than that of SOP1. From the figure 8.1 it seems that as discharge in non-operating hours increases the annual net benefits increases relatively. Fig 8.2 presents the comparisons of the annual power production, the annual power produced by GOOP1 found less as compared to SOP1 because GOOP1 is governed by general release rule while in case of SOP1 the full supply release is give to produce power once the reservoir is filled up to its capacity for the time period t. The power production is function of release and it is directly proportional to release made through turbine and therefore the power production is seen high in case of SOP1.

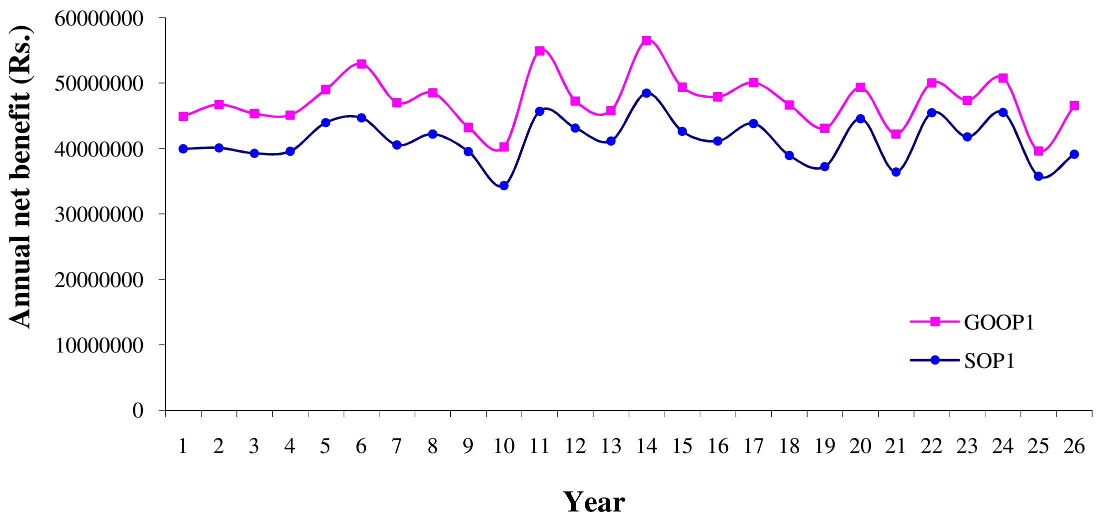

Fig 8.1 Plot of annual net benefit for 26 year.

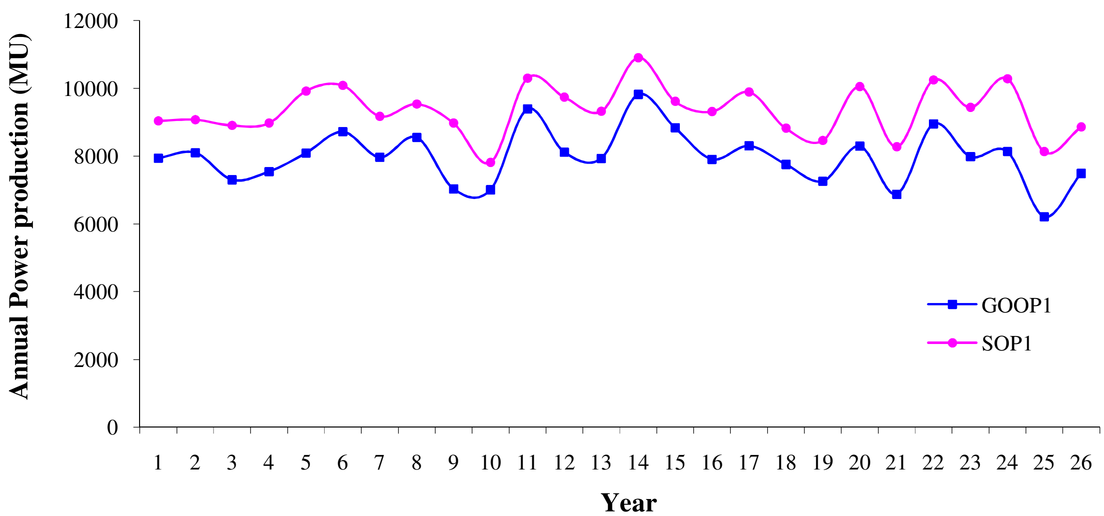

Fig 8.2 Plot showing annul power production for 26 year.

Fig 8.3 shows the curve of power production in the very first year of the study of SOP1 and GOOP1. The power production by SOP1 is higher as compared to GOOP. In pre monsoon and post monsoon periods the power production by GOOP1 is relatively low while in wet period the production of power by GOOP1 is nearly same as SOP1.

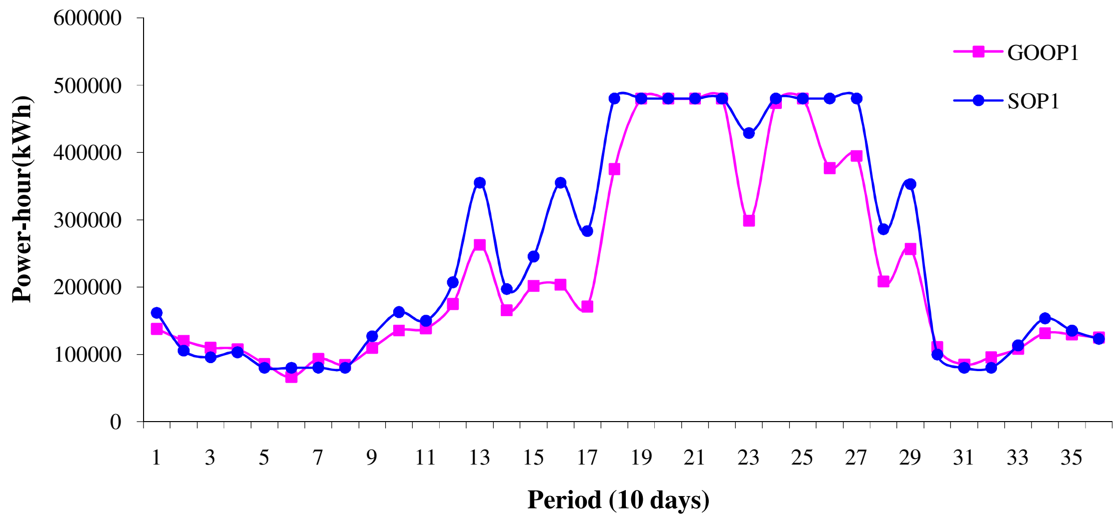

Fig 8.3 Plot showing power production for 1st year

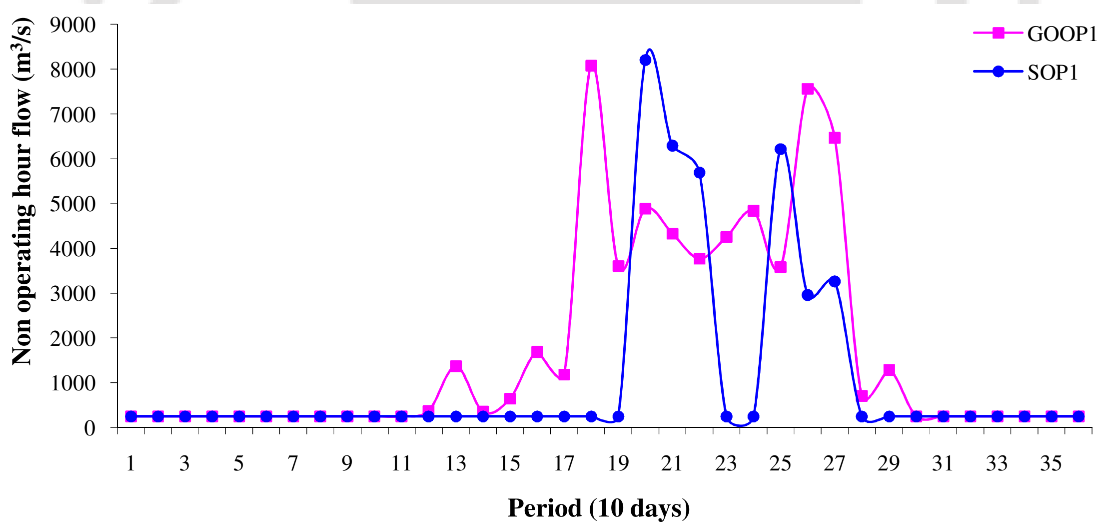

Fig 8.4 Plot of non-operating hour discharge for 1st year

Fig 8.4 gives an idea of the downstream discharge in non-operating hours of the day. The result reveals the operation by SOP1 and GOOP1 is having minimum downstream discharge of the 250 m^3/s in lean period, which is essential to maintain the condition similar to that of pre dam condition and for the survival of the river biota downstream. It seems from the curves that non-operating hour discharge by GOOP1 is comparatively high in pre monsoon and post monsoon period.

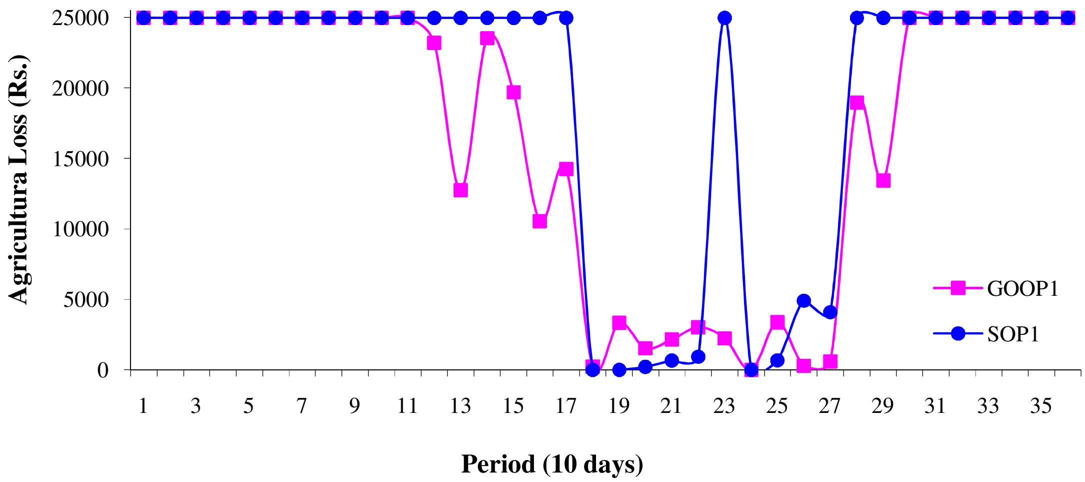

Fig 8.5 Plot of agricultural loss for 1st year

Fig 8.5 is the comparison of the agricultural loss by the different policies. The loss in case of SOP1 and GOOP1 following each other closely in lean period, the loss by GOOP1 is found less in pre monsoon and post monsoon period. It is clear from that loss in cases of GOOP1 and SOP1 the minimum downstream flow of 250m^3/s is ensured in the lean period therefore no loss has been found.

8.5.2 Case –II (DPR2)

The GOOP2 developed for the reservoir operation using multiple regressions (DPR2) is evaluated through SOP2. The simulation is started on first ten day period of month January and with initial storage 1365 Mm^3 (FRL) and the final period of simulation is third ten day period of December. The final output of the GOOP2 and their comparison with SOP2 is shown in Fig 8.6 to Fig. 8.11. The SOP2 means the SOP developed with only 6 m^3/s discharge as minimum downstream environment release in non-operating hours which is negligible discharge but decided to provide by the project management. The annual net benefit from the GOOP2, SOP2 is displayed in Fig 8.6; it becomes clear from the figure, annual benefit obtained by the GOOP2 is relatively higher than that of SOP2. Fig 8.7 presents the comparisons of the annual power production, the annual power produced by GOOP2 found less as compared to SOP2. The power production is function of release and it is directly proportional to release made through turbine and therefore the power production is seen high in cases of SOP2.

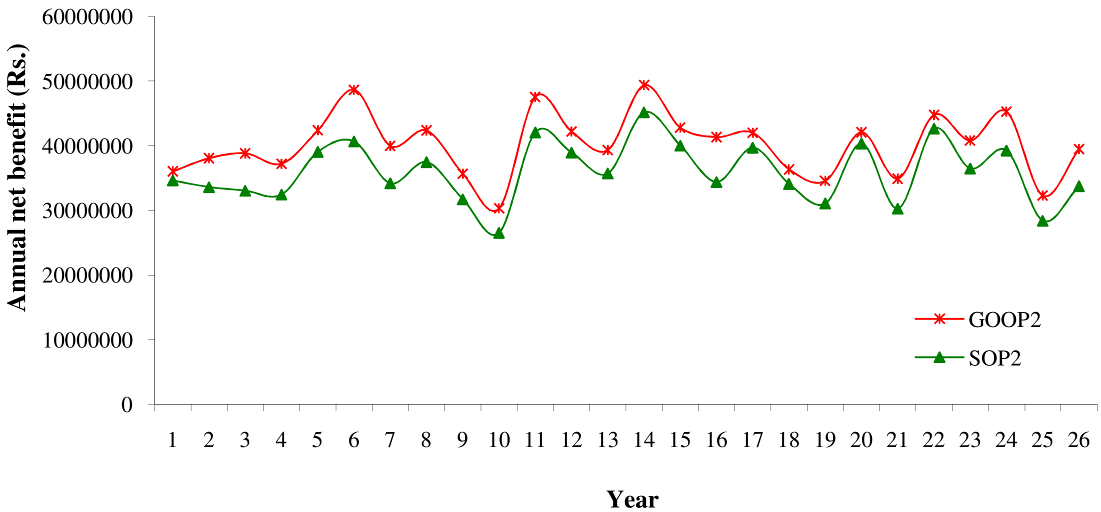

Fig 8.6 Plot of annual net benefit for 26 year

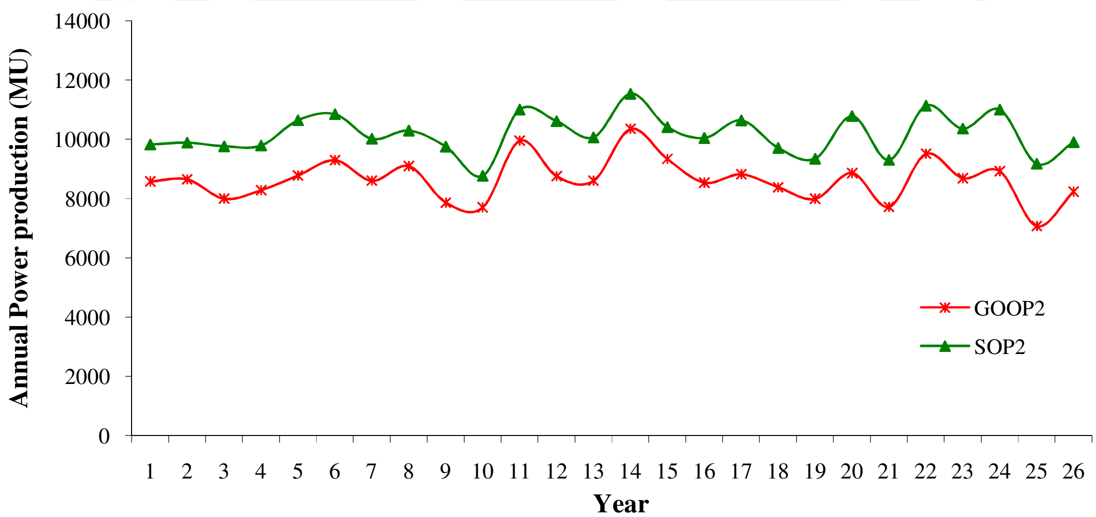

Fig 8.7 Plot showing annul power production for 26 year

Fig 8.8 shows the curve of power production in the very first year of the study, by GOOP2 and SOP2. The power production by SOP2 is seen higher as compare to GOOP2. In pre monsoon and post monsoon periods the power production by GOOP2 is relatively low as compared to SOP2, while in wet period the production of power by GOOP2 is closely following SOP2.

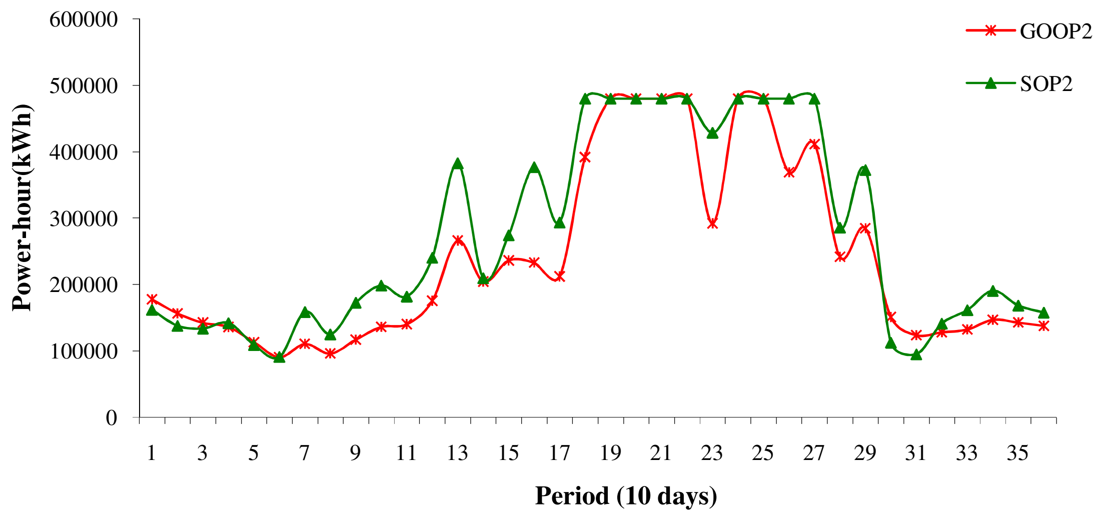

Fig 8.8 Plot showing power production for 1st year

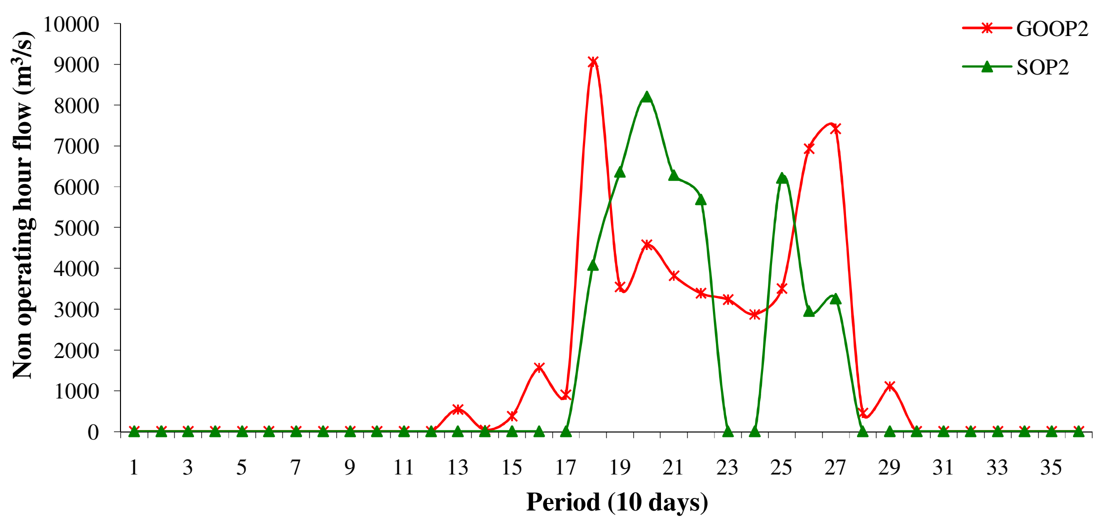

Fig 8.9 Plot of non-operating hour discharge for 1st year

Fig 8.9 presents the scenario of the downstream discharge in non-operating hours of the day. The result reveals the operation by GOOP2 and SOP2, the discharge obtained in pre monsoon and post monsoon by GOOP2 is little high than that of SOP2.

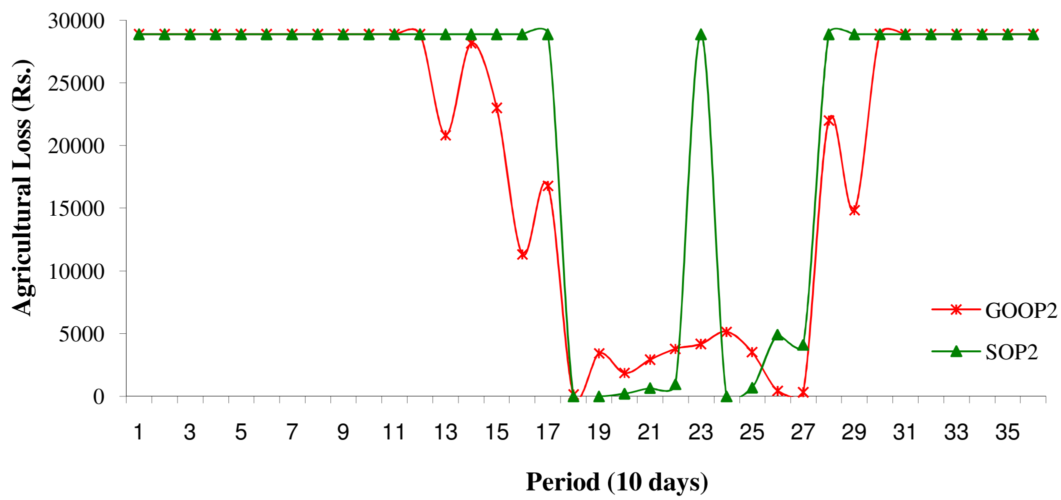

Fig 8.10 Plot of agricultural loss for 1st year

Fig 8.10 is the comparison of the agricultural loss by the GOOP2 and SOP2. In lean period the turbines are operated only to meet the peaking hour demand the agriculture loss in this season is significant as compared to wet season. The loss in case of SOP2 and GOOP2 following each other closely in lean period, the loss by GOOP2 is found less in pre monsoon and post monsoon period because the agriculture loss is function of discharge and in pre monsoon and post monsoon the discharge is relatively more in case of GOOP2.

Fig 8.11 presents the loss of fish production for the first year of operation by GOOP2 and SOP2. It is found from the figure that loss for the fish production is high because the breeding period of the fish is starting from March to June and in the month March, April and May non-operating hour discharge is very less in the downstream which affects the fish production throughout the year.

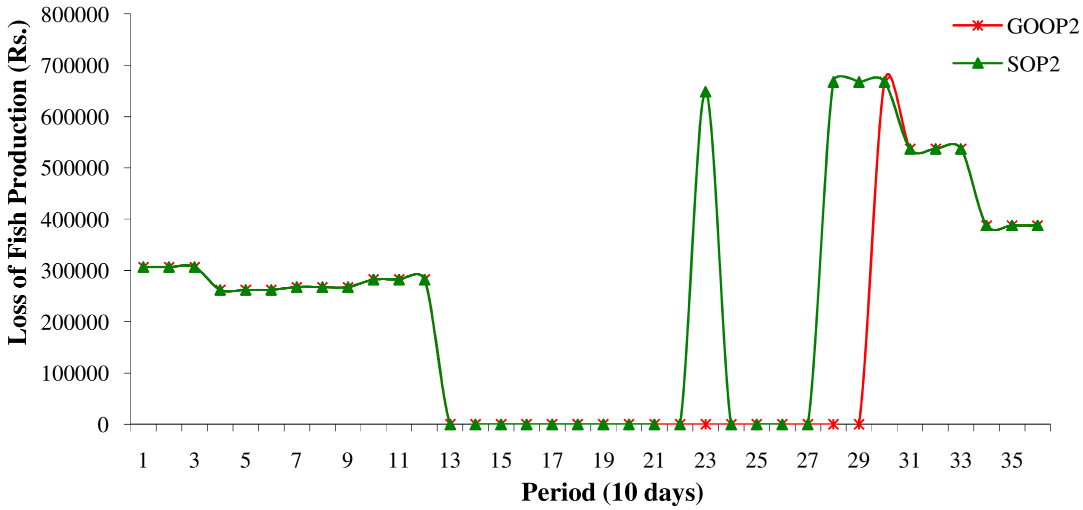

Fig 8.11 Plot of loss in fish production for 1st year

8.6 Conclusion

The general optimal operating policy (GOOP) for two different cases from the deterministic dynamic programming results has been derived for the LSHE project in this chapter. The multiple regression approach called DPR1 and DPR2 because of its simplicity, are used to derive the GOOP1 and GOOP2. The comparison of GOOP is made with SOP. It has been found from the result that annual net benefit obtained using GOOPs are high as compared SOPs, of course with the compromise in annual power production. Though the power production obtained by GOOP2 is relatively low it is sufficient to meet the annual total power demand of the project i.e. 7421.55 MU except in three years. The probability of failing to meet 4 hour peaking power by GOOP2 is 7.80 percent; GOOP1 is 4.48 percent, in case of SOP2 it is found to be 3.80 percent while no failure is seen in case of SOP1. The non-operating hour discharge in the downstream is comparatively high in GOOPs during the transition period of wet and dry season hence loss for the agriculture is slightly low by GOOPs in this period because loss is inversely proportional to discharge.

Table 8.4 Comparisons of different policies

Performance Criteria	SOP1	SOP2	Structural Measure	Nonstructural Measure –I	Nonstructural Measure - II	GOOP1	GOOP2
Net benefit (₹)	41401804	44075376	49279460	47137810	41108256	47379109	40183444
Average Annual Power Production (MU)	10176.09	9349.28	10176.09	9153.35	8505.79	7980.30	8638.61
Minimum Peaking Hour per day	4.00	0.00	4.00	1.14	0.00	1.30	1.39
Minimum Downstream Flow (m^3/s)	6.00	250	417.00	314.00	310.00	250.00	6.00
Probability (%) of failure to meet the 4 hours peaking requirements	0	3.74	0	12.18	69.23	7.80	4.49
Maximum deficit in annual target power production (MU)	0	0	0	0	452.84	1211.02	349.03
% maximum deficit in annual target power production	0	0	0	0	6.10	16.32	4.70

Critical evaluation of the standard operating policy and optimal operating policy considering downstream losses has been carried out based on seven different performance criteria. Table-1 presents a comparison of these alternative operating policies at a glance. Table 8.4 gives a picture about all policies, out of all, the structural measure which is having highest net benefit, highest annual power production, maximum non-operating hour discharge and complete 4 hours of minimum peaking power hour per day, the structural measure proves to be the best policy which can be given first preference for the adoption. However, availability of suitable site, initial capital investment and regular maintenances are some of the practical challenges on the way of implementation of structural measures. Considering requirement of the minimum downstream release, nonstructural measure–I and GOOP1 both are compatible; of course one needs to compare other performance criteria. It's clear from the Table-1 that net benefit and minimum peaking hours obtained from GOOP1 are high as compare to nonstructural measure-I. Also, the probability of failure to meet the 4 hour peaking requirements is less in case of GOOP1. The average annual power production in case of GOOP1 is relatively less, but it is higher than the annual target power requirement of 7421.55MU. Though maximum deficit in annual target power production (MU) and percentage of maximum deficit in annual target power production in case of GOOP1 are 1211.02MU and 16.32 percent respectively and is inferior to nonstructural measure-I, these do not reflect in performance of this policy in peaking hour, which is the prime objective of the LSHE project. Hence GOOP1 can be recommended when implementation of structural measures becomes challenging. Nonstructural measure-I can be recommended when continuous power of 250MW productions throughout the day can be of help in meeting power demand.

Chapter 9

Conclusion, General Discussion and Recommendations for Further Studies

9.1 Introduction

Even though a brief conclusion is presented at the end of each chapter a comprehensive conclusion along with a critical discussion on the research findings of the present study is presented in this chapter. The scope of future extension of the present study has also been outlined in this chapter.

9.2 Conclusion and General Discussion

Systematic literature review has been carried out to study the different aspects of impact of dam operation on downstream environment, synthetic streamflow generation and reservoir operation. Till date lots of studies have been carried out to understand the downstream impact of a dam, but there seems a void for the general procedure which is to be followed for quantification of losses caused due to dam operation. Dam induced diurnal variations downstream may cause many adverse impacts, consequences of which may lead to various losses. If such diurnal variations can be minimized, many impacts downstream can be addressed directly and so the losses. Therefore, in this study an attempt has been made to minimize such diurnal variations through structural and operational measures and same are investigated by its application in LSHE project. Scope of minimizing downstream losses by application of optimization is also investigated using deterministic DP model so that the best alternative for minimizing impact of diurnal variations can be suggested.

The primary objective of the LSHE project is power generation. The project proposes to achieve its objective through annual power generation of 741.55MU by running eight numbers of turbines in parallel and each having 250MW installation capacities. The objective of the flood accommodation may be accomplished with reserve storage of 441.6Mm^3, dynamically varying the storage at each time period t.

Most of the time downstream habitats depend on the river for agriculture, fishing and many other day to day activities. Reduced flow may cause disturbance to them and it may affect income generation and livelihood of the people downstream. Considering all these aspects, assessment of two significant downstream losses has been given more emphasis and quantification of losses from agriculture and fishery is therefore carried out. Mathematical formulation of the problem demands consideration of various aspects of the project. Maximization of the net benefit has been considered as the most logical objective function, so that the project can generate optimal hydropower by considering the downstream impact and consequent losses to maintain the downstream environment, once the project is put in to operation. Considering objective of the project, practical constraints, downstream flow requirements and availability of data, an optimization problem is formulated to develop optimal operating policy which can maximize net benefit and can ensure minimum flow downstream to meet the basic need of aquatic life. The flood control has been set as one of the constraints of the optimization problem by restricting the upper limit of reservoir level at the beginning of any time period t of ten days. The downstream water quality standards are proposed to maintain by supplying minimum release which is given to prevent substantial harmful effects on the aquatic biota and human settlements.

The study of reservoir operation requires long series of streamflow data and in absence of long series of streamflow data, generation of synthetic streamflow is the only choice left. The LHSE project considered in this study has limited data, therefore, 100 years synthetic streamflow has been generated. Generation of synthetic streamflow is carried out using two methods namely ANN and Thomas-Fiering. The performance of the ANN model for the synthetic streamflow generation of the LSHE project with the limited data set has been investigated and its comparison is made with the Thomas-Fiering model considering some statistical parameters viz. (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series. As reservoir operation is generally carried out for different time step, the influence of the time step discretization and selection of input parameters on the synthetic generation of streamflow has been evaluated using both the above said methods. Different models based on input variables and network parameters have been tried and the best model for each time step discretization has been evaluated using above said three statistical measures. The selection of input parameters plays an important role in the streamflow generation. It has been found from the result that the input parameters which have been working well for higher time step discretization models, did not work well for the cases of smaller time step discretization. The results of the study depict that: though periodical mean of the series generated by Thomas-Fiering follows well to the periodical mean of observed series as compared to the ANN model in most of the time discretizations, it gives significant error in case of periodical standard deviation as compared to the ANN generated series. Comparison of skewness of the series generated by Thomas-Fiering and ANN has revealed that the skewness of the ANN generated series is found closer to the skewness of the observed streamflow series for each of these time step discretizations. Out of the three performance criteria; (i) periodical mean, (ii) periodical standard deviation and (iii) skewness coefficient of the series, ANN was found to be performing quite well for the periodical standard deviation and skewness coefficient of the series, while its performance for periodical mean, was also found satisfactory and within acceptable limit. Based on the above analysis, ANN based method can be regarded as a competitive alternative method for generating synthetic streamflow series having potential of better performance as compared to Thomas

Fiering model. It is observed that Thomas-Fiering model gives better results during low flow period in terms of all the three statistical parameters considered in this study. On the other hand ANN model gives better results during monsoon period. Therefore a hybrid model has been generated by utilizing capability of both these methods and a series having close resemblance with the observed series has been generated. The synthetic data generated by using the hybrid model has been used to develop the reservoir operation policies.

Reservoir operation and performance of the system can been visualized through the simulation study. Therefore a reservoir simulation model has been developed to investigate the changed flow regime downstream of a hydropower project. The practical applicability of model has been investigated through its application in LSHE project. The simulation study has revealed that, with proposed power production schedule i.e. with peaking hour of minimum 4 hours, the downstream flow will be varying with a diurnal variation between $6m^3/s$ to $2500m^3/s$ in the lean period. It is important to note that natural flow in river Subansiri in lean period is in order of $500m^3/s$. Such diurnal variation in the streamflow will have adverse ecological effects. During the flood period, diurnal variation induced by the reservoir operation is not that significant and thus will not create any adverse effect. The scope of minimizing diurnal variation through structural and nonstructural mitigation measures have been investigated through simulation study. The reduction in diurnal flow variation can be achieved by introducing a regulating (balancing) pond downstream of the dam (structural measure). Analysis of the downstream terrain has shown that it will be possible to create structure having storage capacity of 36 Mm^3 without raising the tail water level, i.e. without reducing the net head. Similarly scope of minimizing diurnal variation by modifying the operating schedule has been analyzed as a non-structural approach. Two non structural measures were tried in the simulation study. First, one turbine running continuously throughout the day and others running simultaneously for maximum possible duration depending on availability of water (Non Structural Measure-I); second, running one turbine continuously and adding turbines one by one in a way that the each newly added turbine can run for maximum possible hours (Non Structural Measure-II). Comparisons have revealed that structural measures provide the best solution but its implementation depends on many factors like availability of suitable site, availability of fund to meet initial investment and the maintenance cost. Non-structural measures-I has also been found to provide notable improvements over the baseline standard operation scenario.

The deterministic dynamic programming technique has been applied for maximization of net benefits considering different losses downstream due to hydropower project. The multiple linear regression approach has been used to infer the general optimal operating policy. After extensive trials over linear and non linear regression models the DP with multiple linear regression approach called DPR has been found most suitable and hence used to derive the general optimal operating policy (GOOP). Two polices were attempted. One considering mandatory release of 250m^3/s to meet various environmental need and the other considering 6m^3/s mandatory release as proposed in the project. The "GOOP1" represent the GOOP developed using the constraint of minimum downstream environmental release as 250m^3/s in non-operating hours while "GOOP2" symbolize the GOOP developed with only 6m^3/s discharge in non-operating hours as proposed in the project. The general optimal operating policies (GOOP1 and GOOP2) for two different cases have been derived from the deterministic dynamic programming results for the LSHE project. The comparison of GOOP is made with the standard operating policy (SOP). It has been found from the result that annual net benefit obtained using GOOPs are high as compared to SOPs, of course with the compromise in annual power production. Though the power production obtained by GOOP2 is relatively low it is sufficient to meet the annual total power demand of the project i.e. 7421.55MU except in three years out of 26 years. The probability of failing to meet 4 hour peaking power by GOOP2 is 7.80 percent; GOOP1 is 4.48 percent, in case of SOP2 it is found to be 3.74 percent while no failure year is found in case of SOP1. The non-operating hour discharge in the downstream is comparatively high in GOOPs during the transition period of wet and dry season hence loss for the agriculture is low by GOOPs in this period.

Critical evaluation of the standard operating policy and optimal operating policy considering downstream losses has been carried out based on seven different performance criteria. Out of all, the structural measure which is having highest net benefit, highest annual power production, maximum non-operating hour discharge and complete 4 hours of minimum peaking power hour per day proves to be the best policy which can be given first preference for the adoption. However, availability of suitable site, initial capital investment and regular maintenances are some of the practical challenges on the way of implementation of structural measures. Considering requirement of the minimum downstream release, nonstructural measures–I and GOOP1 both are compatible, of course one need to compare other performance criteria. It's clear from the Table-1 that net benefit and minimum peaking hours obtained from GOOP1 are high as compare to nonstructural measure-I. Also, the probability of failure to meet the 4 hour peaking requirements is less in case of GOOP1. The average annual power production in case of GOOP1 is relatively less, but it is higher than the annual target power requirement of 7421.55MU. Though maximum deficit in annual target power production (MU) and percentage of maximum deficit in annual target power production in case of GOOP1 are 1211.02MU and 16.32 percent respectively and is inferior to nonstructural measure-I, these do not reflect in performance of this policy in peaking hour, which is the prime objective of the LSHE project. Hence GOOP1 can be recommended when implementation of structural measures becomes challenging. Nonstructural measures-I can be recommended when continuous power of 250MW productions throughout the day can be of help in meeting power demand.

9.3 Recommendations for Further Studies

Looking to the present status of the work the following possibilities are there for the further extension of the present work.

1. In the present study only two losses i.e. agriculture and fishery are being considered for quantification, as livelihood of majority population of downstream depends upon these activities. Many other losses such as, loss of forest, loss of riparian zone, reduction of water for domestic use, poor nutrition and hygienic conditions, uncertainty of income and increase in stress, which are not quantified here can be taken up for detail study. River Subansiri is recognized as, having highest potential for the tourism viz. river rafting, site seeing of Dolphin etc. So, it can be an interesting study to work out the monetary return from such tourism aspects; even the creation of reservoir may increase the tourism upstream of the dam.
2. Performance of general optimal operating policy has been analyzed using deterministic dynamic programming technique. The objective function in the present study has been formulated for maximization of net benefit considering power benefit and two major losses i.e. agriculture and fishery. Capability of the traditional and heuristic optimization techniques can be explored to examine scope of having better optimal operating policy. In the present study single state variable has been used. Optimal operating policy can also be developed by considering both storage and inflow as state variable.
3. Scope of improving the ANN based method for synthetic streamflow generation can be investigated further by considering different network parameters such as, increasing number of hidden layer, changing the training algorithm, varying the activation function for wet and lean season and changing type of network.

4. The detail investigation to validate the loss function using the data from the existing project can be carried out in future. Because the project is under development stage and hence the post operation data is not available presently.

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APPENDIX-I

Input data used in different models	SOP1	SOP2	GOOP1	GOOP2
Minimum mandatory dam release	$6m^3/s$	$6m^3/s$	$6m^3/s$	$6m^3/s$
Environmental release	$250m^3/s$	-	$250m^3/s$	-
Crop coefficient	0.90	0.90	0.90	0.90
Yield response factor	0.95	0.95	0.95	0.95
Data of fish production	Given in Table 4.2			
Evaporation rate	Varying from 1.87mm/day-5.88mm/day depending on the time period in a year			
Streamflow	Ten day Streamflow series of 20 years generated by using Hybrid model and 6 years daily observed data (2002-2007) averaged over ten days			

PUBLICATIONS

International Journal

1. Maya, R.R. and Sarma, A.K. (2010) "Minimizing Diurnal Variation of Downstream Flow in Hydroelectric Projects to Reduce Environmental Impact" *Journal of Hydro-Environment Research* (In Press). doi:10.1016/j.jher.2010.12.001

2. Maya, R.R. and Sarma, A.K. "Influence of Time Step Discretizations on the Generation of Synthetic Stream Flow Using ANN Model." *Water Resources Management*, (Under Review)

3. Maya, R.R., Sarma, A.K. and Singh, V.P. "A Hybrid model for synthetic streamflow generation." *Water Resources Management*, (Under Review)

4. Maya, R.R. and Sarma, A.K. "Assessment of downstream impacts and quantification of loss for a hydroelectric project."(to be communicated)

5. Maya, R.R. and Sarma, A.K. "Operation of a reservoir considering downstream losses of a hydropower project."(to be communicated)

Conferences

1. Maya, R.R. and Sarma, A.K. "Reservoir Optimization for Mitigating Downstream Impact of Dams built on a Tributary of the Brahmaputra" International Conference organized by: Core Professional Group for the Brahmaputra (CPGB) 18^{th} -19^{th} December 2010, Hotel Gateway Grandeur, G. S. Road, Guwahati.

2. Maya R.R.and Sarma, A.K. "Simulation Study for Minimizing Diurnal Variation of Flow in a Hydroelectric Project to Reduce Downstream Impact" Proceeding 3^{rd} Perspective on "Current & Future State of Water Resources & The Environment "organized by The Environmental and Water Resources Institute of American Society of Civil Engineers and Indian Institute of Technology Madras, Chennai, Tamilnadu 5^{th} - 7^{th} January 2010, Page: India/2010/000927-37.

3. Maya R.R. and Sarma, A.K. "Artificial Neural Network Based Synthetic Stream Flow Generation Model" Proceeding of 3rd International Conference "Current and Future State of Water Resources and Environment" organized by The Environmental and Water Resources Institute of American Society of Civil Engineers and Indian Institute of Technology Madras, Chennai, Tamilnadu 5th- 7th January 2010, Page: India/2010/000942-52.

4. Maya R.R. and Sarma, A.K. "Synthetic Stream Flow Generation Model using Artificial Neural Network Technique." Proceedings of the National Seminar on "Recent Advances in Hydrology for Water Resources Development and Management" Organized by *Association of Hydrologist of India* held at The M.S. University, Baroda, Gujrat on "21st - 22nd January 2009, Paper no 2 them-1 (Surface Hydrology) Page:14-32.

5. Sarma, A.K. and Maya, R.R. "Reservoir Project in North-East India: Scope and Constraints."Proceedings of the National Seminar on "Reservoir Planning & Operation" organized by Assam Engineering College, Guwahati, Assam, India 19th December, 2007, Page:14-19.