B. TECH. PROJECT REPORT

On

The value of adaptive policies for reservoir operations

BY

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DISCIPLINE OF CIVIL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

December, 2019

The value of adaptive policies for reservoir operations

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

of
BACHELOR OF TECHNOLOGY
in
CIVIL ENGINEERING

Submitted by:
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Guided by:
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INDIAN INSTITUTE OF TECHNOLOGY INDORE
December, 2019

CANDIDATE’S DECLARATION

I hereby declare that the project entitled **“The value of adaptive policies for reservoir operations”** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in ‘Civil Engineering’ completed under the supervision of Dr. Munir Ahmad Nayak**, Assistant Professor, Discipline of Civil Engineering,** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Name:

Signature:

Date:

_CERTIFICATE

It is certified that the above statement made by the students is correct to the best of my knowledge.

Dr. Munir Ahmad Nayak

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Preface

This report on "The value of adaptive policies for reservoir operations" is prepared under the guidance of Dr. Munir Ahmad Nayak.

Through this report, we have tried to find the validity of dynamic adaptive policymaking using a new algorithm in reservoir management by cross validation with historically available data. The approach can be used to make policies for short-term operation as well as for the long-term adaptation of real-life reservoir problems [3].

We have used the best of our abilities and knowledge to collect and manipulate most appropriate data along with providing proper assumptions wherever required. The report contains plots and figures that make interpretation easier.

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Acknowledgements

I would like to express my deep and sincere gratitude to my B. Tech. Project supervisor Dr. Munir Ahmad Nayak for his kind support and valuable guidance to complete my theses work effectively and on time. His feedbacks help me improve a lot.

I wish to thank everyone who directly or indirectly helped me to complete this project, especially Ms. Rosa Vellosa, Mr. Waqar ul Hasan, Mr. Shalay Guptha and Mrs. Sakiba. It is their help and support, due to which I became able to complete the project and technical report.

I am always thankful to my parents and relatives for all the unconditional love and supports they have given. Without their support, this report would not have been possible.

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Abstract

Critical assessment of outdated policies is essential in water management issues for a deeply uncertain world. Various approaches are being proposed and experimented to find reasonable solutions for water management problems. In this report, we use an algorithm in which policies are represented in the form of a binary tree. Operations are carried out in minimizing flood risks and maximizing water availability for municipal water supply, irrigation, industrial development and as for hydropower production. We found thresholds for flood and demand deficit, by considering the damages due to these disasters we assigned appropriate penalty as cost functions. We used summation of squared differences of demand with release during each deficit (Large deficits are more dangerous) and flood discharge is multiplied with a large constant (preventing flood is more important than preventing deficits). The summation of these two gives the cost function or objective function. Algorithm runs in a way that it will reduce the objective function along with increased number of function evaluations. We used a dynamic adaptive optimization-simulation approach on historical data by separating the long-time horizon (28 years) into short intervals of five years. Optimized policies are applied on each short interval to find release decision for each day. The results show that the algorithm is successful in minimizing the demand deficits but fails to prevent large floods. The approach can be applied to real-life policymaking, with a proper assumption of plausible future scenarios. The application of this approach in real-life situations requires the consideration of more available data for mass balance in a reservoir and more indicators to govern the policies in order to reduce the flood damages. Our approach is reasonable since demand deficits are reduced over time, though more research is required to devise optimal policies that minimize flood damages. Future work should focus on using additional available information in to the simulation-optimization model. The algorithm takes time to run in a machine with limited RAM, and the problem of local optimum values arise and the algorithm stops converging for a longer time. This will result in a policy with non-satisfactory performance. The use of parallel computing and running the algorithm in multiple nodes will help to reduce these problems, but a higher-performing cluster is needed for the same.

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chapter 1

Introduction

Meeting water demands and mitigating risks of natural disasters such as floods and droughts-(6) are serious concerns of all times. Water managers started planning and constructing infrastructures such as reservoirs for storing water, distributing it, and for preventing large floods. Once the calendar was invented and seasons and weather cycles became tame, the approach was easier. These traditional aggressive approaches for water management had not envisioned their negative impacts on the environment and unreasonable distribution among the population. Even though numerous benefits were derived from the reservoirs, these approaches could not solve the issue of meeting the basic demand for water in many cases such as good quality drinking water. More than one billion people lack access to safe drinking water and around 2.4 billion lack access to adequate sanitary services-(11). The number of deaths due to water-related issues remains so high.

Additional demands due to rapid growth in population and consequent agricultural and industrial growth made it impossible for old policies to meet modern demands. Anthropogenic climate changes worsen the situation as in an increased frequency of extreme flood and drought events in India-(4).

It is required to seriously assess the functionality of the traditional reservoir operation policies and modify them to satisfy increased demands and uncertain and limited supply of water. The hard-path is an approach that focuses on meeting water management objectives through centralized facilities like infrastructure development. Reducing demands instead of seeking endless supply is possible through a soft-path approach that will complement the centralized facilities with small decentralized facilities like the involvement of stakeholders in decision making, implementing marketing and pricing to ensure efficient use and equitable distribution of water and using new technology-(11). Recently various approaches such as Adaptive Robust Design (ADM)-(8), Simulation Optimization Approach-(7), Dynamic Adaptive Policy Pathways-(9), etc. and a combination of more than one of these are proposed and experimented at various locations to discover the solutions for this unresolved water-related issues.

In this project, we use a case study of the Rengali reservoir situated in the Angul district of Odisha. We use the Dynamic Adaptive Policy Pathways-(9) approach that combines Adaptive Pathways and Adaptive Policymaking. Adaptive pathways use different assumptions of future scenarios and develop release decisions for the worst scenario. Tipping points are important in adaptive policy making and triggering actions will be there at each tipping point. In dynamic adaptive policymaking using the objectives and uncertainties in the future after finding the possible opportunities and vulnerabilities and their approximate time of occurrence we will find out monitoring actions. From all this information finding out different adaptive pathways will be easy, and the decision-maker will choose the most preferred pathway. Since this pathway has the capacity to monitor changes that were not expected by triggering actions termed as contingency actions (for example: a reassessment, corrective actions, defensive actions, and capitalizing actions) it will be a dynamic adaptive pathway-(9).

For simulation and optimization, we use an algorithm which is derived from Distributed Evolutionary Algorithm in Python (DEAP), in which policies are represented as binary trees called policy tree and a better performing policy tree will be selected by random generation and iteration-(7). Optimization and simulation performed with a historical period with the objective to fit historical releases result in a policy that approximately mimics the historical release decisions, and accuracy of mimicking the observations increased while increasing NFEs. Dynamic adaptive approach results in policies that show reduced risks of flood and drought compared to the static policy that is being used in the Rengali since its start.

The convergence of the algorithm requires a number of function evaluations to yield a near optimal policy and the process is time-consuming. The local optimum values result in unsatisfactory release decisions. To avoid these problems multiple nodes can be used. To obtain the best policies for future operations suitable projections of plausible scenarios can be used. An advantage of this approach is when we want our policy to consider more objectives such as hydropower generation, maintain water level for transportation (ship, boats, etc) and groundwater table level maintenance we can use the same algorithm by assigning more indicators and appropriate cost functions.

Chapter 2

Literature Review

Twentieth-century water management policies are based on constructing large infrastructures in the form of dams, conduits, reservoirs and pumps to store and transport water. Even though this hard path approaches had numerous benefits, they had their drawbacks-(11). The environmental, social and economic costs of these approaches are so large. An increase in water demand due to rapid population growth and consequent evolution in agriculture and industrial sector made it impossible for traditional approaches to work efficiently. The climate change due to human exploitation on the environment transforms the supply of water more uncertain. A soft path approach that complements centralized facilities (facilities planned and implemented by the authority to provide benefits to the public) with some decentralized actions is on the way. Examples for decentralized actions in soft path approaches include using efficient technology to reduce wastage of water in agriculture, industries, and domestic purposes, including marketing and pricing on the water–distribution, encourage efficient and equitable use of water, and including stack holders in decision making-(11).

A skillful forecast of future helps planners to devise the best performing operation policy for reservoir management. As mentioned by Stedinger (1984), stationary and non-stationary Stochastic Dynamic Programming are two algorithms derived from traditional Stochastic Dynamic Programming (SDP)-(6). Non-stationary SDP results in optimal release for each month based on the conditional distribution of future inflows. Stationary SDP relies on available inflow for policymaking. Non-stationary SDP found more efficient than stationary SDP. Stationary SDP with the current period's inflow is found more efficient than non-stationary SDP with the preceding period's inflow-(6). Snowpack, lake level, soil moisture, groundwater, and streamflow information should be considered to improve the efficiency of the SDP algorithm. We will initially choose some policies to examine, and these algorithms can only optimize the policies that are examined. The best policy cannot be made when the policies chosen were not skillfull enough-(6). To overcome these shortcomings we can use soft-wares that can produce several random policies and optimize a policy for release decisions that can be made. This will reduce the chance of missing the most appropriate policy. Policy tree optimization that uses policies in the form of binary trees with indicator nodes and action nodes-(7). Indicator nodes have conditional statements with their corresponding thresholds and have two outputs which are either indicator node or action node. The policy tree optimization algorithm performed better than the traditional algorithm Stochastic Dynamic Programming (SDP) but slightly less than Deterministic Dynamic Programming (since DDP uses perfect foresight information, so we can only expect the performance of any other approach getting closer to this)-(7).

The work done by Nayak et al., (2018) has the aim of combining the use of future forecast and use of recharging ability of groundwater for policymaking. Reforecast data for the short term can be used to simulate ensemble forecast for the long term. This simulated synthetic short-term forecast ensemble replicates the errors in the observed forecast-(10). The operating policy should be optimized across plausible forecasts rather than a single future scenario-(10). After optimization, to ensure the robustness (Strength to optimize the objectives) of optimized policy, it can be reevaluated through a process called simulation, in which policy is applied on the same time horizon from which the policy is optimized to find modified-release decisions. So that we can compare the failures in both observed and optimized release data and ensure that which one is more robust-(10). Due to the increased uncertainty of environmental cycles, the traditional best guess approach for future scenarios are no longer sufficient. Multiple plausible futures are required-(13). To obtain a policy that performs well with the change in the future, a combination of Adaptive Policymaking and Adaptation Pathways-(9) can be used. Adaption pathways are based on tipping points and their sell-by date (approximate time of occurrence of tipping points). The adaptation pathway approach represents a sequence of suitable actions after a tipping point like a tree, and any route through this tree is called as an adaptation pathway-(9). The adaptive policy making is an approach that will design dynamic adaptive plans. In this approach, the values of variables available (in current state) are used to specify future objectives. After that possible opportunities and vulnerabilities in the future along with their time of occurrence (approximate) are determined. Then selecting actions appropriate to each vulnerability and opportunity is being done. Mitigating actions for likely vulnerabilities, hedging actions for unlikely vulnerabilities and seizing actions for likely opportunities are some of such actions.

But still, there is a possibility of unforeseen future events, to monitor that we give additional actions called contingency actions. These actions include reassessment, corrective actions, defensive actions, and capitalizing actions. The approach that combines adaptive pathways and adaptive policy making is termed as Dynamic Adaptive Policymaking-(9). Dynamic adaptive policy pathways can deal with changing (unforeseen) conditions. It is efficacious and cost-beneficial.

Chapter 3

Objectives

There had been a lot of attempts to find reservoir operation policies that give optimal benefits from all of its purposes. It is better to keep our policy in a way that is economic, cause the least environmental damage and meet the water demands of different stakeholder groups. Optimizing the reservoir for multiple uses is not easy. One way to achieve this is assigning corresponding cost functions to each failure mode and choosing a policy that minimizes the summation of these cost functions.

Our aim is finding reservoir operation policies adaptive to the changes in environment, economic and social changes. We use a policy tree algorithm and dynamic adaptive optimization and simulation approach to minimize flood risks and maximize water supply for irrigation as well as for hydropower production. To mitigate flood damage addition of a large penalty should be done. Choosing a squared value of deficit may help in reducing big droughts since a small deficit is manageable.

Before changing the policy of a specific reservoir, one should know the shortcomings of the current policy. If the method we will use is efficient enough to overcome these shortcomings we can say our approach is successful in the study area. If it fails re-evaluation should be done all the input parameters, constraints, and thresholds we used.

Chapter 4

Study Area

The location of the Rengali dam is at 21˚ 16’ 36” N latitude and 85˚ 01’ 57” E longitude (5), in Angul district of Odisha. A map of the Rengali dam along with its watershed is shown in Figure 1. The dam is 70.5 m high and 1040 m wide. Rengali reservoir formed behind the dam is the second-largest reservoir in Odisha. The dam was constructed in 1985 across Brahmani River and the reservoir started functioning since 1988. The Rengali reservoir has a total catchment area of 30, 03, 000 hectares, and an annual mean rainfall of 1570 mm is observed on the catchment. At the full reservoir level of 123.5 m high, the reservoir has a surface area of 37,840 hectares (5).

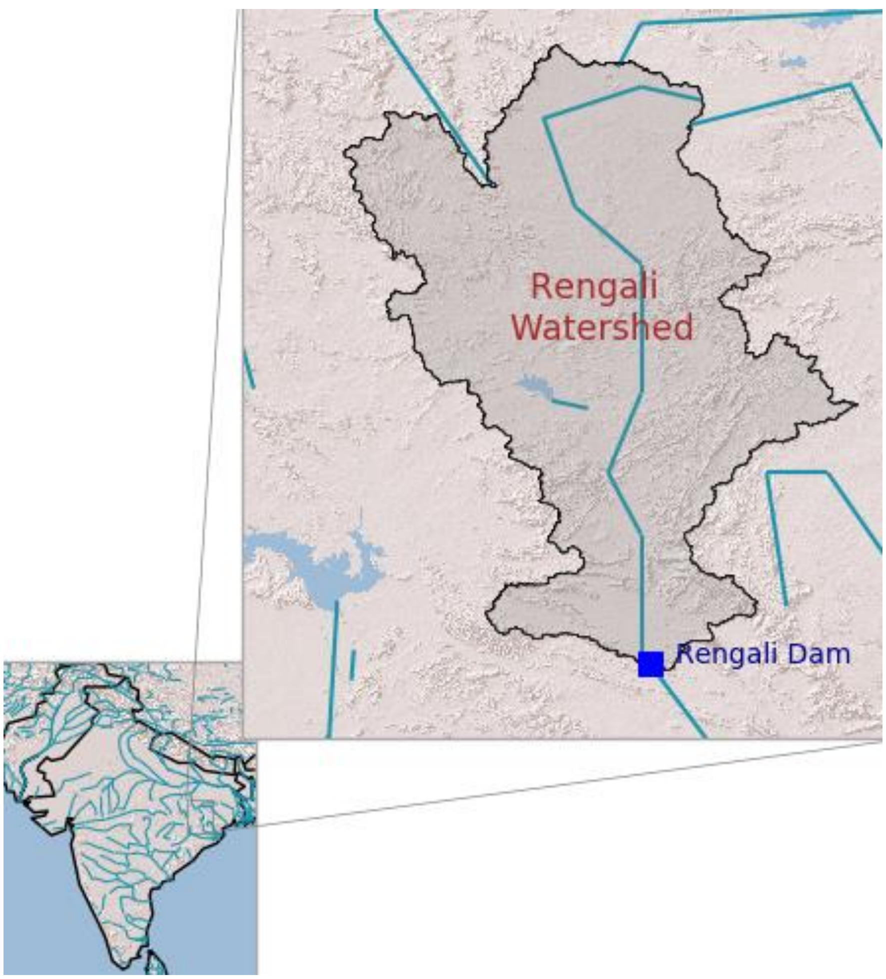

Figure 1: Location of Reservoir and the watershed of the dam

But due to global warming and consequent deviations in the path and time of tropical and monsoon wind, the weather in Odisha became deeply uncertain.

The current policy that is used to decide the trigger actions in the Rengali reservoir is a rule curve that describes the approximate water level of each day based on traditionally obtained weather cycles. The weather of Odisha falls under the category of tropical monsoon type. Summer (March-June), Autumn (July-September) and the Winter (October-February) are three major seasons in the area. The peak temperature in summer ranges from 30-40˚C. South-west monsoon acts from July to September may cause floods during the starting days of July. The state experiences a small amount of rainfall from returning monsoon in October and November but January to March are dry. Table 1 gives some characteristics of the Rengali reservoir. An average cross-section of Brahmani river downstream to the Rengali reservoir is shown in Figure 2.

Table 1: Hydrologic and Hydraulic characteristics of Rengali Reservoir

S. No	*Property*	*Value*	*Unit*
1	Height of dam	70.5	m
2	Width of dam	1040	m
3	Area at full level	37,840	hectares
4	Area at mean level	28,000	hectares
5	Mean annual rainfall	1570	mm
6	No. of turbines	5	
7	Capacity of each turbine	50	MW
8	Water holding capacity at Full reservoir level(FRL)	3412×10^6	m^3
9	FRL	123.5	m
10	MDDL	109.72	m
11	Spillway capacity	46,960	m^3/s
12	Catchment area	25,25,000	hectares
13	Free catchment at barrage site	4,78,000	hectares
14	Total catchment	30,03,000	hectares

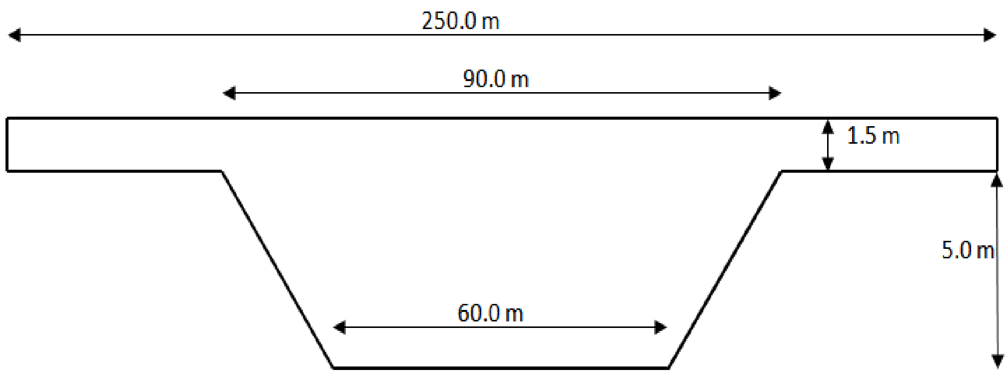

Figure 2: Average cross section of Brahmani river downstream to Rengali reservoir (11)

Chapter 5

Methods

5.1 Data

Inflow, outflow, precipitation, power production and storage details of the Rengali reservoir from 1988 to 2015 are used. Apart from this rule-curve of the Rengali reservoir that tells the level of the reservoir that should be maintained in a day, stage versus level curve that tells the volume of water in the reservoir at each level and spillway rating that gives the outflow through spillway gates relative to the level of the reservoir. Water demand for a day (from January 1 to December 31 represented as 1 to 366) is taken as the smoothed average outflow for each day in every year ranging from 1988 to 2015. For smoothing seven-day moving mean can be used.

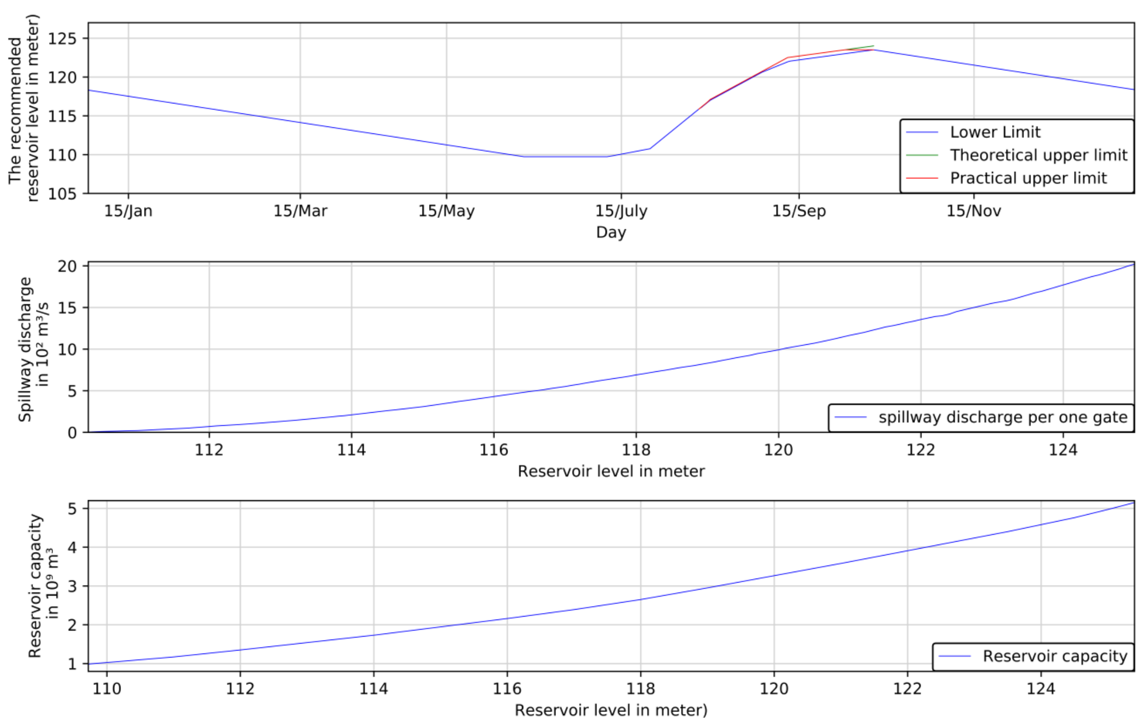

Figure 3: Rule-curve, Spillway discharge, Stage versus Level for Rengali Reservoir

5.2 Analysis of Performance of the Current policy

Currently, the Rengali reservoir operations are based on a rule-curve that gives the reservoir level that should be maintained in a day. Rengali is running on the rule-curve since 1988.

To ensure the requirement of a new policy we need to check if there are any variations in the climate or if the current policy meeting the objectives properly or not. The inflow data from 1988-01-01 to 2015-07-21 can be divided into five-year intervals in each, after finding 30 days moving average of the data. From each five-year intervals, the mean value of the data for each day can be calculated. We will plot these mean inflows for each 5-year interval on an inflow versus day plot. This plot gives the presence of seasonal shift as time passes. The Variation of total inflow with respect to year gives the trends in precipitation if any.

The outflow should not exceed spillway capacity and safe downstream flow. So we will choose the minimum of both as the threshold for outflow. Safe downstream flow is the maximum flow possible without causing any damage to the most vulnerable part on downstream. This can be approximately estimated using the Manning's equation by considering the average trapezoidal dimensions given in Figure 2, and choosing manning's coefficient 'n' for downstream as 0.035 from assuming a natural formation of the river bed and considering the fact that 'n' will increase along with depth, due to linear increase in roughness with respect to flow depth-(4) .

$$Q_{sd} = \frac{1}{n} A R^{\frac{2}{3}} S^{\frac{1}{2}} \tag{1}$$

$$Q_t = min\{Q_{sd}, Q_s\} \tag{2}$$

$$Q_{out} \geq Q_t \qquad \leftrightarrow \text{ Flood} \tag{3}$$

Here Q_{sd} is safe downstream flow, n is average manning's constant (or roughness coefficient) for river bed, A is area of cross-section of trapezoid assumption, R is hydraulic radius, S is average slope of river bed, Q_s is the spillway capacity of Rengali dam, Q_t is the outflow threshold for flood and Q_{out} is the outflow during a day. A plot of data versus day for each five-year batch together gives the information about any seasonal shift that happened. After finding a daily average, 95th percentile, and 5th percentile of flow characteristics (for inflow and outflow), through taking seven-days moving average we can smooth the curve.

Here we are assuming that the average outflow for each day is the average demand of that day. So we refer to the smoothed curve of the average total outflow for daily demand. During days with a release lower than the demand for water of that day, we will approximately find the deficit for demand as the difference between demand and release as shown in equation 4.

$$D_e = \begin{cases} D_i - Q_{out} & \forall \quad D_i > Q_{out} \\ 0 & \forall \quad D_i \leq Q_{out} \end{cases} \tag{4}$$

$$\overline{{D_e}^2} = \frac{\sum {D_e}^2}{T} \tag{5}$$

Here D_e is the demand deficit on a day, D_i is the demand for each day i, Q_{out} is the outflow during that day and T - is the time horizon, i.e. the total number of days in the interval. Equation 5 gives the daily average of squared deficits throughout the time horizon. We square the deficits to ensure that damage due to higher deficits are much higher but smaller deficits are adjustable.

The number of days each year with a deficit can be calculated and assigned on the corresponding year. But flood events generally happen for longer duration, we assume a minimum of 5-days gap between each flood incident and count the number of floods in a year.

5.3 Algorithm Used

We are using a policy tree algorithm in which policies are represented as a binary tree (7, 10). Each tree contains indicator nodes and action nodes or terminating nodes. Indicator nodes contain a conditional statement with an indicator variable (variables we are using in our algorithm such as available flow, day of a year, etc.) a tipping value for this indicator. According to the binary outputs of the conditional statement (True or False) an indicator nod further maps into two nodes (each one can be either an indicator node or an action node). An action node is generally represented as a leaf of the tree (the tree is inverted) contains an action in the given set of actions. These actions save our policy from failing to meet objectives when needed. Figure 3 is an illustrative example of a policy tree. In the algorithm, multiple random binary trees are generated, using the indicators and actions we input. Other natural processes like cross-over, mutation, and pruning are done on each parent to create child trees and cut out unwanted branches from trees. Among the population of policy trees, the algorithm compares the cost function of each child policy with that of its parent tree and returns the one with a minimum cost function, since our objective is the minimization of demand deficits as well as flood events. In this experiment, we used a population size of 100 with several parents, μ =10. The maximum depth of the tree is limited to 6 and cross over probability is 0.70. Features used are S_{t-1} (previous day's storage) and day of water year (dowy: here, a water year starts from 1st January and end on 31st December and dowy will be counted from 1 to 365 or 1 to 366 for leap years). Release demand and hedging actions are used as action triggers as shown in Table 2.

Table 2: Actions used for reservoir operations and their descriptions

Actions used	Description
Hedge_60	Release only 60 % of demand
Hedge_70	Release only 70 % of demand
Hedge_80	Release only 80 % of demand
Hedge_90	Release only 90 % of demand
release_demand	Release total demand
release_excessCP	Release water excess to spill way level

5.4 Algorithm Efficiency

While the optimization objective is to fit with historically observed values, the algorithm converges in a way that the square of the difference of optimized storage values and simulated storage values with respect to observed values is minimal. A plot of objective function (average of the squared difference between observed values and simulated values during the same period) verses NFE (number of function evaluations); gives an idea about converging efficiency. The optimized policy is obtained with a two-hundred thousand NFE on a 20-year time span starting from 01-01-1994 and ends at 31-12-2013. This policy applied to simulate the reservoir releases during the same period. Comparison between observed storages and releases helps in gaging the convergence of the algorithm

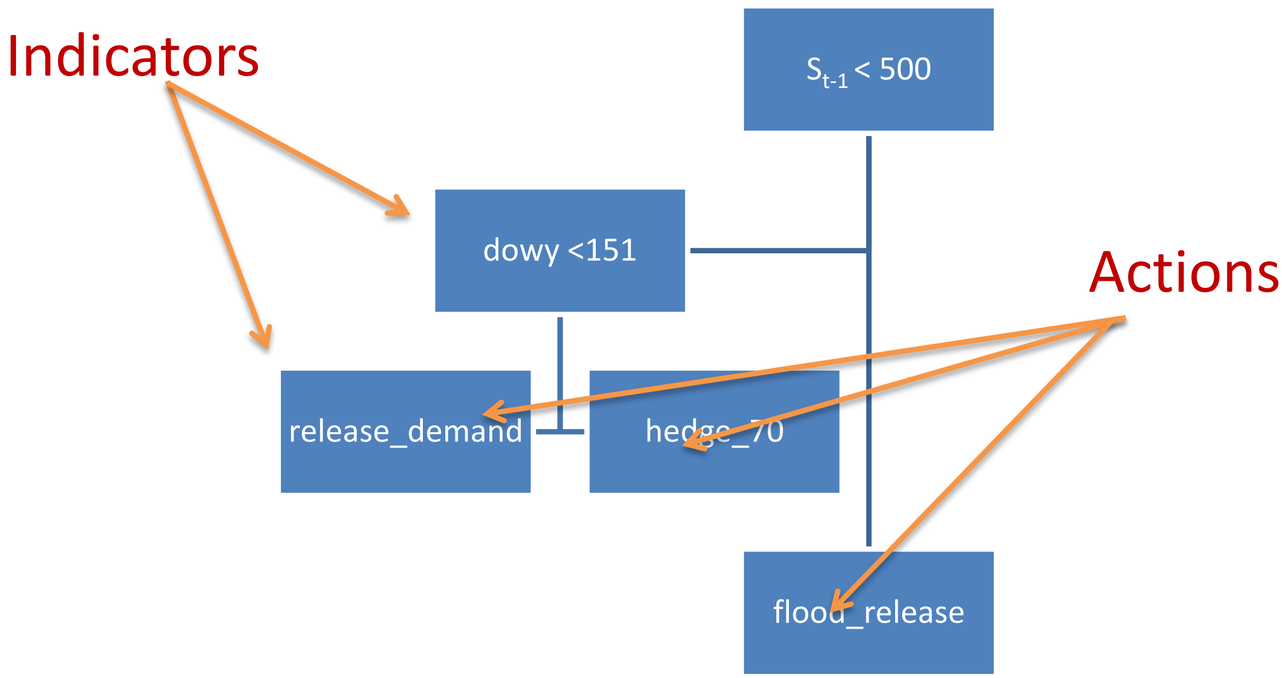

Figure 4: Policy-tree representation of policies (7, 10).

5.5 Problem Formulation

When our objective is to minimize demand deficits and flood events, penalty values are assigned for losses due to demand deficits and flood discharges. The cost function for these objectives is given in equation 7. Squared values of deficits are used since higher deficits cause significant damages, while smaller deficits are adjustable. Demand deficit at a particular day "i" is represented as d_i. For flood, a large multiplier to prevent flood at any cost is assigned. "Q_i" is excess flood release and "c" is large-value constant that ensures preventing floods are more important than ensuring water supply.

$$Cost\ function\ =\ \sum \boldsymbol{d_i}^{\boldsymbol{2}} +\ \boldsymbol{c}\ *\ \boldsymbol{Q_i} \tag{7}$$

When our objective is to obtain a policy that will result in releases matching with historical releases the cost function is the average of the square root of squared differences between observed and optimized storages as shown in equation 8. Here $S_{i,sim}$ is the simulated storage at day "i" and $S_{i,obs}$ is the observed storage of the same day. T is time horizon varying from the first day to the last day of the time interval we have chosen (1, 2, 3, ….)

$$cost\ function\ =\ \frac{\sqrt{(\boldsymbol{S_{i,sim}} - \boldsymbol{S_{i,obs}}\,)^2}}{\boldsymbol{T}} \tag{8}$$

5.6 Dynamic Optimization and Simulation

The reservoir data are available for a period of 28 years from 01-01-1988 to 21-07-2015. We divided this time horizon into five-year intervals. Release decisions for each one of these short intervals (except for the first short interval ranging from 01-01-1988 to 31-12-1992) were estimated using an optimized policy obtained from observed data of historical period. Since we change our policy after every five years to consider the changes happened in the environment, this approach is both adaptive (adaptive to climate change) and dynamic (modification in 5-year intervals). Then the total number and magnitude of flood events and deficits in each year of this obtained release were found. A comparison of this data with total flood and deficit in each year that is actually observed gives the reliability of the dynamic adaptive approach.

Chapter 6

Results & Discussion

6.1 Analysis of Performance of Current Policy

From the observed data, it is evident that seasonal shift is real and functioning of the current policy is not satisfactory as shown in Figure 5, Figure 6 and Figure 7. In Figure 5, the entire time horizon is split in to 5-year intervals. After this average inflow during each day for each interval is calculated and plotted. When the peak of 1988-1993 (light salmon) and 1993-1998(salmon) curves found around the 225th day (August-12), the peak of 2008-2003 is found around the 250th day (September-6) of water year. Even though there is not so much change in the duration of monsoon a gradual change in its peek can be observed with respect to time. The amount of inflow is getting reduced with passing time, since 1991 to 1993 were drought years-(3)). Figure 6 a and 6 b show a decreasing trend in inflow characteristics as time pass.

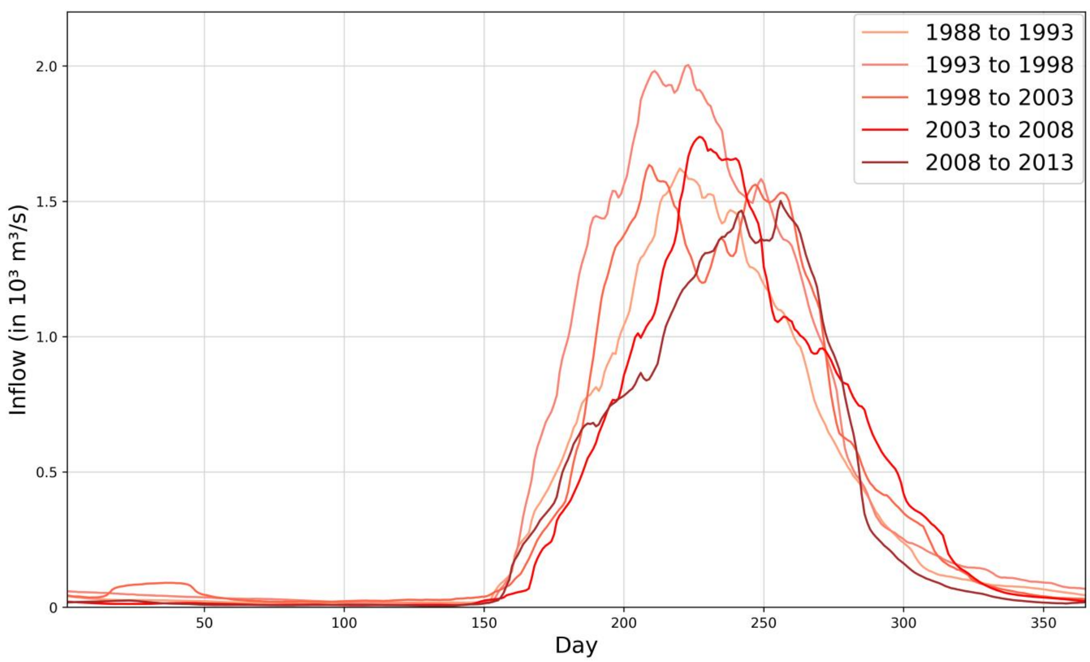

Figure 5: 30-days moving average of inflows for 5-year intervals from 1988 to 2013

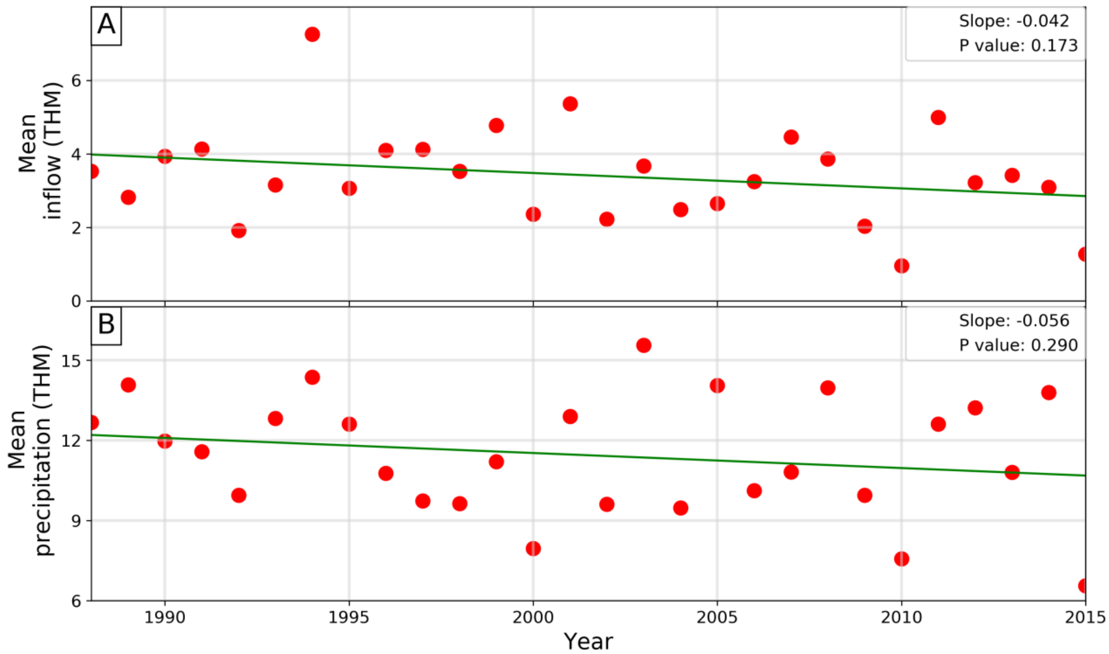

Figure 6: a) Trends in mean inflow b) Trends in mean precipitation

Seven days moving average of daily, 5th percentile and 95th percentile values of total outflow, outflow through the spillway, outflow through the power channel and inflow to the reservoir are shown as in Figure 7. In Figure 8 total deficits in a year, the total power generated in a year and total flood events happened in a year are plotted. When a drought happened in 2010-(10), the water supply and power generation were considerably lower than the normal (Figure 8). Even though the reservoir provides a minimum outflow for the power generation throughout the year, there were some large outflows through power channels during peak monsoons (Figure 7). To avoid overdesigning the power channel (constructing with a capacity more than required, need more cost) or to avoid damages to power channel the excess flow through power channel should be regulated.

From these figures, it is evident that the seasonal shift and inability of the reservoir in meeting the objectives requests a change in current rule-curve based policies. A dynamic model that updates the policy after a short time interval using the increased observations and adaptive to the climate changes should help in managing the reservoir better.

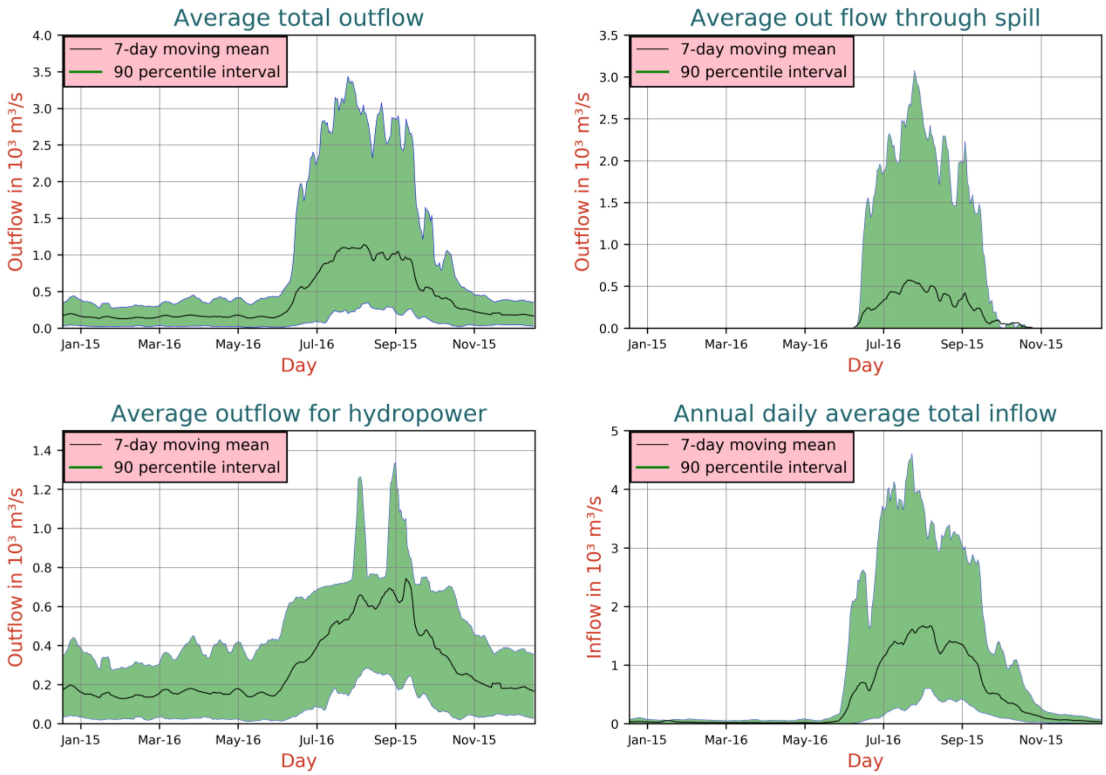

Fig 7: Daily average, 5th percentile and 95th percentile of a) total outflow, b) outflow through spillway c) outflow through power channel and d) inflow after smoothing the curve with seven- days moving mean.

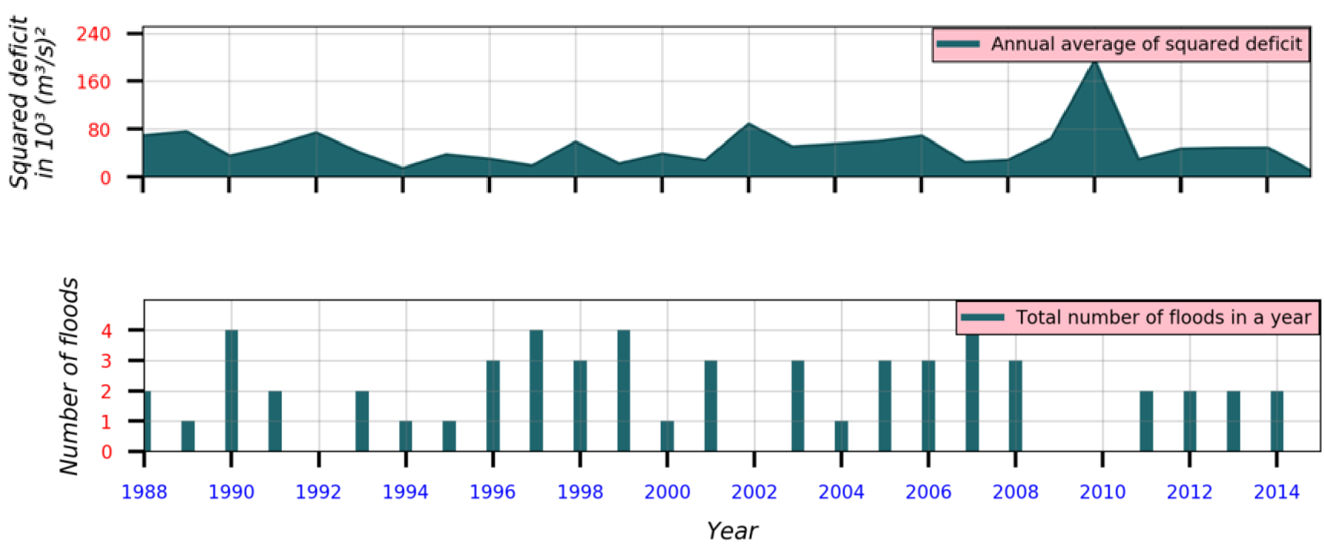

Figure 8: a) Annual average of squared deficit versus year, b) Total number of floods versus year in the Rengali.

6.2 Algorithm Efficiency

The plot of objective function versus the number of function evaluations (Figure 9), shows that the objective function converges as the number of function evaluations (NFEs) increases. Figure 10 A is a comparison of optimized release with the observed releases. The optimized results approximately coincide with the observed flows except for the peak flows. Figure 10 B is a comparison of optimized storages to that of observed storage, the maximum capacity of the reservoir is also shown as a red line. Both these figures showing that observed and optimized values are coinciding. Our objective was to fit with historical data without using rule-curve. The figure shows that the optimized curve follows the observed releases closely. Whenever the observed storage deviates from the rule-curve optimized curve also shows a deviation. But observed storages and optimized storages still do not match. This is because the objective function value is still around 60. Further running the algorithm till we get a satisfactory value of objective function will make observed storage values and optimized storage values much closer.

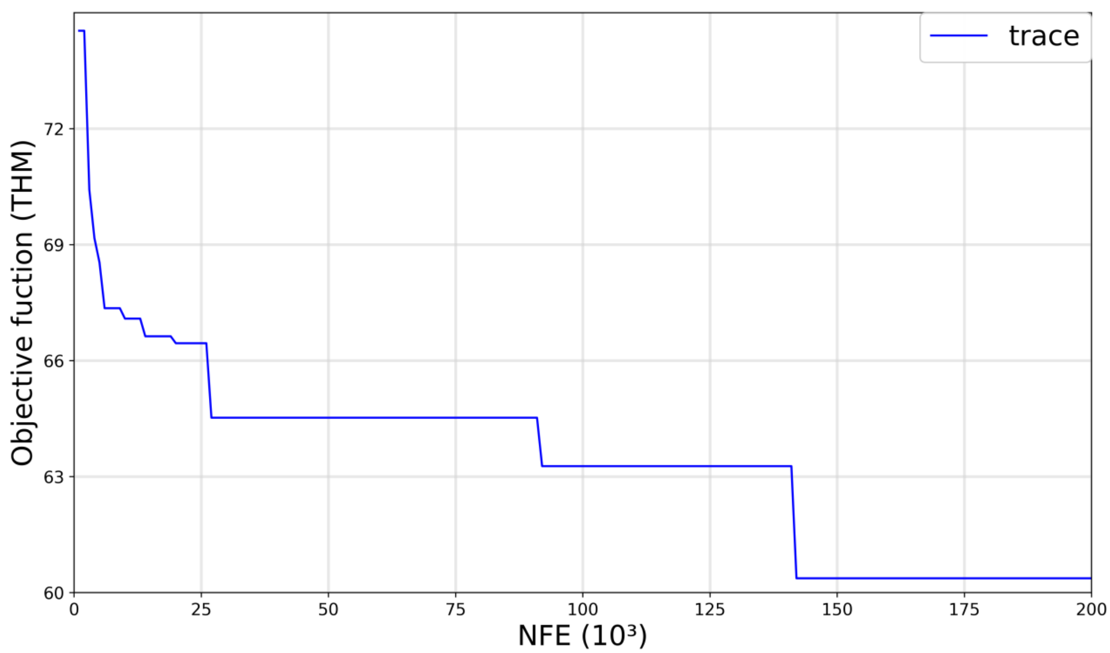

Figure 9: Objective function versus number of function evaluations.

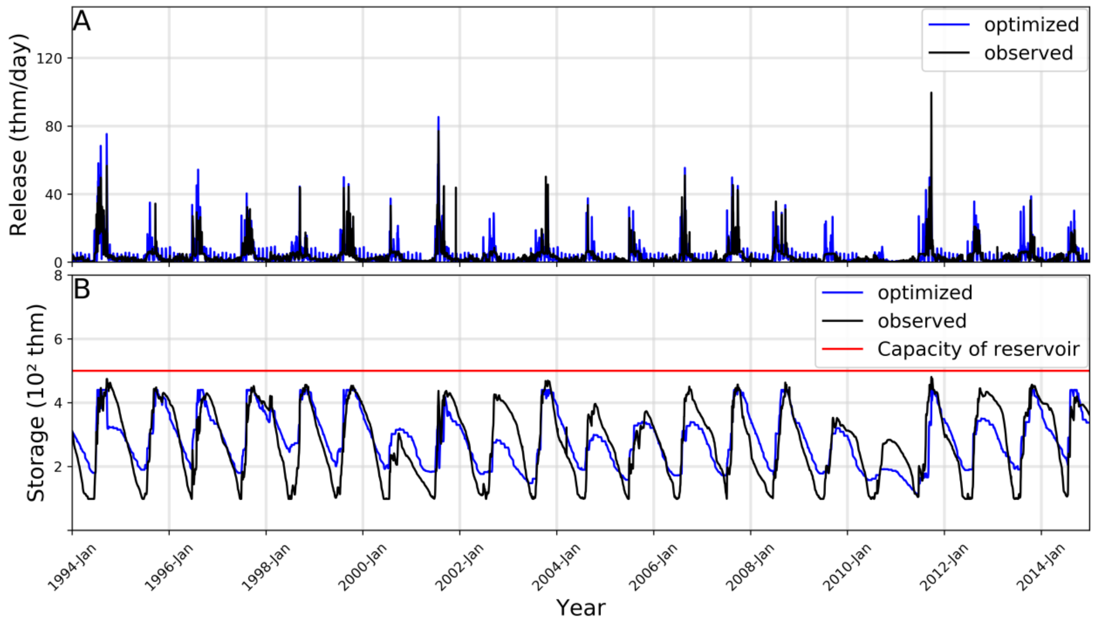

Figure 10: a) Optimized and observed releases versus day, b) Optimized and observed storages along with capacity of reservoir versus day

6.3 Dynamic Optimization and Simulation

Along with an increase in the number of function evaluations the demand deficit can be minimized. The flood risk does not show a satisfactory reduction as in Figure 11, though a high cost for flood damage is assigned in the objective function. Figure 11 b shows a considerable reduction in deficit but still during 2010, when there was a considerable drought, even our approach does not result in a large reduction in deficits. Floods do get reduced over time except for extreme flood events as in Figure 11 a.

Further studies are required to examine why the algorithm is only optimizing relatively small risks and not working well for the most extreme events. This might be a problem in the choice of indicators and assigned threshold values, the variables such as infiltration, channel precipitation, and evapotranspiration should be considered for a more accurate mass balance for the reservoir storages. Neglecting such variables may underestimate the flood magnitudes in simulation periods.

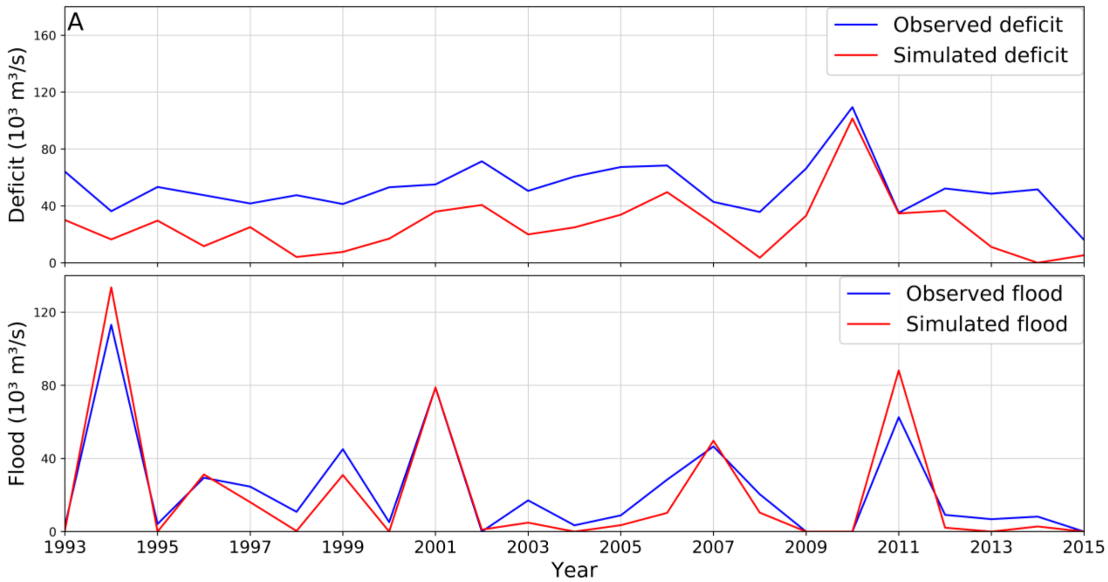

Figure 11: a) Observed and optimized demand deficits with respect to year. b) Observed and optimized values of total flood in every year ranging from 1993 to 2015

Chapter 7

Conclusion and Future Remarks

Finding operating policies for water management that negotiate the uncertainty due to climate shift and increased demand is certainly needed. In this report, we used a dynamic adaptive policymaking approach using a policy tree algorithm. The objective is to estimate the efficiency of the dynamic adaptive approach in optimizing release decisions for a reservoir to minimize flood risks, maximize the water supply for irrigation and maximize power production in a study area. In this project, we consider supply for irrigation, industrial, and household uses and water needed for hydropower production together as total water demand, and simulation-optimization was carried devise policies to reduce flood risks as well as unmet demands. The results show that the algorithm can minimize demand deficits reasonably well but failed to prevent the flood risks. In these operations, we are considering only the day of water year and previous day's storage as indicator variables. Consideration of other indicator variables such as precipitation, infiltration, and evaporation is also essential, since neglecting them will have a significant impact on flood magnitude. Modification of the algorithm is needed to consider all these parameters, and flood mitigating actions, such as flood releases. Future work should focus on improving the algorithm from all the shortcomings so that it can be applied to real-life problems.

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