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A Bi-level Neuro-Fuzzy System

Soft Computing for Reservoir Operation

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Abstract

Reservoir operation studies purely based on the storage level, inflow, and release decisions during dry periods only fail to serve the optimal reservoir operation policy design because of the fact that the release decision during this period is highly dependent on wet season water conservation and flood risk management operations. Imperatively, the operation logic in the two seasons are quite different. If the two operations are not sufficiently coordinated, they may produce poor responses to the system dynamics. There are high levels of uncertainties on the model parameters, values and how they are logically operated by human or automated systems. Soft computing methods represent the system as an artificial neural network (ANN) in which the input- output relations take the form of fuzzy numbers, fuzzy arithmetic and fuzzy logic (FL). Neuro-Fuzzy System (NFS) soft computing combine the approaches of FL and ANN for single purpose reservoir operation. Thus, this study proposes a Bi-Level Neuro-Fuzzy System (BL-NFS) soft computing methodology for short and long term operation policies for a newly inaugurated irrigation project in Gidabo Watershed of Main Ethiopian Rift Valley Basin.

Keywords: *Bankruptcy rule, BL-NFS, Reservoir operation, Sensitivity analysis, Soft computing, Water conservation.*

1 Introduction

In hard computing one has to deal with a large set of conventional techniques such as mathematical, stochastic and statistical methods. In contrary, soft computing combines biological structures like human knowledge including recognition, understanding, learning, and others into the computing. Soft computing is an approach to construct computationally intelligent techniques, such as Fuzzy Logic (FL), Artificial Neural Networks (ANNs) and Neuro-Fuzzy System (NFS) that lead in to the possibility of constructing intelligent systems such as autonomous and automated designed systems techniques (Sonawane et al, 2013).

In early attempts to assist reservoir operations, models were developed with detailed physical characterization of climate-soil-plant interaction proposed by FAO (Dudley and Burt, 1973; Smout and Gorantiwar 2005; Singh, 2014; Difallah et al., 2017). For multi-crop irrigation Vedula and Nagesh Kumar (1996) proposed SDP model. Both excess and insufficient allocation of water resources that do not promote optimum and timely agricultural plant water uptake are due to knowledge gaps between farmers' experiences on water application and that actually consumed in the root zone.

Reservoir operation is a complex problem that is often challenging for water resource planners and managers because it involves many decision variables, multiple objectives as well as considerable risk and uncertainty (Saliha, 2012). Determination of irrigation reservoir operating policies is a complex problem because of uncertainty involved in the inflow, upstream and downstream demand, climatic and environment conditions, crop water intake, soil moisture content, etc.

Reservoirs play an important role in irrigation water management, as they have major storage facilities and release outlets for storing the excess water during rainy periods for later deficit during dry season, sometimes for extended drought years (Jiang et al., 2015). The purpose of a storage reservoir is to transform the random and periodic natures of flows into a series of releases that more closely correspond with the seasonal water demands for irrigation agriculture (Kumar et al., 2006; Consoli et al., 2008). This objective is achieved by regulating the amount of stored water and by passing flows through the reservoir outlet works to farm units. Flow regulation takes an uncontrolled flow, such as water flowing naturally from river or barrage and turns it into controlled releases from a reservoir to fully or partially satisfy seasonal irrigation water demands.

Reservoirs are operated by means of rule curves that relate time dependent storage level and release based on the amount of inflow, irrigation demands and downstream flow regulation (Shiau and Lee, 2005; Klipsch and Evans 2007; Gebresenbet, 2015). To assist planners in predicting the behavior of a water supply network consisting of reservoirs, junctions, river reaches, diversions and demand sites, models are built as simulation models, optimization models or a combination of the two (Mirchi et al., 2009). Dynamic Programming (DP) is a widely used mathematical modeling technique to determine the optimum allocation of scarce resources among multiple competing sectors.

The use of more accurate decision support tools like reservoir simulation and optimization modeling from historical and forecasted water availability scenarios helped to overcome the limitations. Farmers lack sound knowledge of on-farm water management, particularly on how much to irrigate and when to irrigate as they tend to over-irrigate at times of abundances and stress crops unnecessarily at times of water shortages leading them to conflicts in other parts of the schemes. The difficulty also arises from the complexities of water supply system design and the difficulties to control water flow for different irrigation technologies (Tulu, 2003).

The reason why the soft computing techniques have been used for deriving operating policies for reservoir operations is to decrease the dimensions of the problem and propose more flexible decisions to changes in system dynamics. These techniques can be advantageously employed to handle such problems when conditions of the systems are uncertain. New research directions have found very efficient soft computing techniques in handling large uncertain data like large-scale reservoir operation (Sonawane et al, 2013). Operating policies developed by using soft computing techniques showed very good results in terms of water saving and sustainable water management.

2 Related Work

To shift to irrigation technologies, several irrigation development projects are under construction in Ethiopia such as Kesem-Tendaho, Koga, Rib, Gidabo, Megech-Sereba, Kobo-Girana, Raya-Azebo and Adea-Betcho and sooner or later will be operational. Ethiopia is increasingly investing in irrigation sector in order to exploit the agricultural production potential of the country to achieve food self sufficiency at the national level, to generate foreign currency from export earnings and to satisfy the raw material demand of local industries (Birhanu et al., 2015).

The newly inaugurated Gidabo Dam Irrigation Project (GID) in the Central Rift Valley Basin of Ethiopia is subjected to water-related conflicts. GID is looking forward to begin cultivation of a number of proposed crops with specified crop calendar and specified percentages of land allocated to each crop. By enabling production twice or three times a year the project creates irrigation supply to more than 79,000 farmers and fish farming for many others. There are a number of other user sectors mainly small and medium level irrigation projects in the upstream areas, more than 400 coffee processing plants, more than 15 urban cities and towns and rural population throughout the watershed, livestock productions, beneficiaries of Lake Abaya in the downstream area of Arba Minch in the forms of aquaculture production, water transportation or recreation. All these users rely, in one way or the other, on the water resources in the Gidabo Watershed.

Thus, due to the complications of the water user sectors and their water intake rate, it is almost impossible to build a near optimal reservoir operation policy for GID using hard computation methods. Furthermore, there are no long time historical data that relate water inflow, reservoir storage level and release for GID Reservoir. The socioeconomic conditions and the base of hydrology pattern during planning of the reservoir construction have changed overtime. The project area updated the irrigation plan several times and therefore may not operate according to the water allocation target during feasibility studies and there are needs to adapt to changes. Here comes the need to use soft computing methods that are more advantageous over hard computing.

Furthermore, the water allocation to GID reservoir takes hierarchical nature at the watershed level and at the farm level that give a bi-level decision making problem. The water supply authority determines the water allocation target while the environment protection authority determines to minimize the flood risk throughout the watershed. The GID reservoir was meant to play both purposes.

In bi-level multi-objective programming, managers/planners at upper level allocate the water based on certain criteria to lower-level decision makers (DMs); dispatch their decision to lower level DMs who allocate the water to different competing uses, thereby making it a hierarchical decision making problem (Masood et al. 2021). Masood et al. (2021) analyzed several applications of bi-level programming on water resource allocation for different basin studies including a bi-level fuzzy goal programming proposed by Redi et al. (2020) for planning agro-processing water allocation in Gidabo Watershed.

The agro-processing study was restricted to sampled data from upper and middle sub-watersheds in Sidama and Gedeo regions of the same study area to allocate water to coffee processing plants, coffee farmers and consumers. The possible extensions of this study are to conclude from sampled data to the population data for all coffee processing plants and also extension of the study to all kinds of agro-processing productions like food processing, oil refinery, sugar production and beverage. The methodology efficiently incorporated capacitated two-stage production and dynamic inventory control optimization (TSP-DICO) to the soft computing methodology for water allocation decision.

The coffee processing plants also compete for water during dry season with the downstream irrigation water project GID. The two productions are uncoordinated and uncooperative unless they are sufficiently communicated. In the current study, a bi-level soft computing methodology is proposed for reservoir operation. One has to understand the similarities and differences between the two related studies to fully understand the system dynamics by putting the two models in series or parallel to come up with unified concussions.

3 Problem Formulation

3.1 Variables definition

Indices

t	Period: $1, 2, \ldots, T$
n	Planning years
T_1	End of wet season
T_2	End of dry season
T	End of planning year
j	Neural network used for the operation

Input variables

${D^{nt}}_j$	Net irrigation water demand for reservoir operation
${I^{nt}}_j$	Net water inflow to the reservoir

Artificial variables

${d^{nt}}_j^{-}$	Irrigation water deficit above the inflow
${d^{nt}}_j^{+}$	Excess inflow of water above irrigation demand

Constants

DSL	Reservoir minimum storage (dead storage) level
ASL	Reservoir active storage (conservation storage) level
FCL	Reservoir maximum storage (flood control)
CCL	Canal capacity limit
M m^3	Million Cubic Meter

Output variables

${V^{nt}}_j$	Reservoir storage level
${V^{nT_1}}_j$	Reservoir maximum storage level at the end of wet season
${V^{nT}}_j$	Reservoir minimum storage level at the end of dry season
${x^{nt}}_j$	Water release from the reservoir and inflow
${y^{nt}}_j$	The overflow from the reservoir spillway
${z^{nt}}_j$	Water diverted from the inflow

3.2 Input layer: water demand and supply analysis

For each time period t, either $D^{nt}{}_j \leq I^{nt}{}_j$ or $D^{nt}{}_j > I^{nt}{}_j$. The annual agricultural production cycle is divided into two growing seasons: a wet season $t = 1, 2, \dots, T_1$ in which rain falls on agricultural land and flows into the reservoir. If $D^{nt}{}_j \leq I^{nt}{}_j$, the water supply is larger than the irrigation demand and it may mean that t is a "wet season" in which case the excess water $d^{nt}{}_j{}^{+} = I^{nt}{}_j - D^{nt}{}_j$ could be permanently stored in the reservoir for future deficit periods. On the other hand, during dry months rainfall is at a minimum and the base inflow is not sufficient to meet the irrigation demand of the project area. That is why the reservoir is built with associated appurtenant structures. Otherwise, agriculture without reservoir may face crop failure and drought. If $I^{nt}{}_j \leq D^{nt}{}_j$, the water supply is smaller than the irrigation demand and it may mean that t is a "dry season" in which case the water deficit $d^{nt}{}_j{}^{-} = D^{nt}{}_j - I^{nt}{}_j$ may be fully or partially released from the reservoir to meet the irrigation demand during this period. This classification is fuzzy in its nature and may vary according to the hydrological, meteorological, environmental, socioeconomic conditions, catchment area, other competent users, political and man-made decisions, etc. The water demand for irrigation also depends on farm size, irrigation technology, irrigation efficiency and losses, crop water demand, season of the year, etc. Different combinations of these fuzzy parameters lead to different operation conditions of the reservoir.

3.3 Objective function and constraints

The objective functions of the bi-objective reservoir operation model are minimization of the total deficit for the water conservation goal and minimization of the maximum of the overflow for any period for flood risk management goal.

The constrained dynamic reservoir operation used for the study was proposed by Güntner et al. (2004) given by

$$V^t{}_j = V^{t-1}{}_j + z^t{}_j + (P - E)A^t{}_j - x^t{}_j - y^t{}_j \quad (1)$$

In equation (1) above $V^{t-1}{}_j$ is beginning period storage level while $V^t{}_j$ is end of period storage level. $z^t{}_j$ is the diverted water from inflow $I^t{}_j$ from an upstream reservoir or catchment area. The term $(P - E)A^t{}_j$ may be positive or negative depending on whether t is in a wet or dry season where P and E are precipitation and evaporation rates to or from the reservoir surface area $A^t{}_j$. $x^t{}_j$ and $y^t{}_j$ are the decision variables of reservoir release and overflow respectively.

The first constraint of the model is the release decision at any period should not exceed the irrigation water demand i. e. $x^t{}_j \leq D^t{}_j$ or in fuzzy terms the difference between the release and the demand should be "small". The other constraints are the reservoir and canal capacity limits, $\mathrm{DSL} \le V^t{}_j \le \mathrm{FCL}$ and $0 \le x^t{}_j \le \mathrm{CCL}$. In fuzzy terms DSL is assigned 0 fuzzy membership degree for storage level, while FCL is assigned the highest membership degree of 1. Similarly, release decision "small" gets fuzzy membership degree 0, while release decision "high" closer to CCL gets the highest fuzzy membership degree of 1. The objective functions of the Bi-Level Neuro-Fuzzy System (BL-NFS) reservoir operation model are water conservation and flood risk management. For the water conservation goal, minimization of the total of the squares of the unmet irrigation water demands are considered while for the second goal, minimization of the maximum of the monthly overflows is considered.

In the BL-NFS reservoir operation model, a variable FCL was obtained from all the inflow-demand pairs when the water level at any time reaches above this limit the reservoir has either to release "high" irrigation water or else deliberately overflow to downstream non-beneficial uses. Similarly, variable DSL is obtained from all the inflow-demand pairs when the water level at any time reaches below this limit, the reservoir can no more release water or deliberately overflow. Thus, the feasible reservoir operation rule curves lie between the two limits. The reservoir ASL is determined as the maximum of all the deficits during dry season obtained by the backward operation logic. The release decision at any time is made by observing the beginning period storage level, inflow and irrigation water demand in relation to variable DSL, FCL and ASL.

The objective function for the water conservation operation is minimization of the sum of the squares of the water deficit/excess to all cropped area given by equation (2).

$$\min \sum_{n=0}^{N} \sum_{t=T_1}^{T} \left(d^{nt}{}_j{}^{-} - \left(V^{n(t-1)}{}_j - V^{nt}{}_j\right)\right)^2 \qquad (2)$$

The interpretation of equation (2) is the difference between the volume drop and irrigation water demand is irrigation deficit and it has to be sufficiently "small".

The objective function for the flood control operation is minimization of the maximum of the overflow beyond the flood control limit given by equation (3).

$$\min_{n,j} \max_t \left(d^{nt}{}_j{}^{+} + V^{n(t-1)}{}_j - V^{FCL}{}_j\right) \qquad (3)$$

The interpretation of equation (3) is the difference between the beginning period storage level plus the incoming excess water and the flood control volume level should be sufficiently "small".

3.4 Single objective optimization using neuro-fuzzy system

It has always been difficult to model the multi reservoir system using classical Stochastic Dynamic Programming (SDP), due to curse of dimensionality inherently associated with it. The fuzzy inference system employed for the current study were suggested by (Sonawane et al, 2013), originally proposed by Panigrahi and Mujumdar (2000) and it includes the following functional steps for each of the enhanced bi-level neuro-fuzzy system soft computing method.

Step 1: A fuzzification interface that transforms the crisp inputs into degrees of match with linguistic values. This includes fuzzification of available inputs, in which the crisp inputs such as the inflow, reservoir storage and release were transformed into fuzzy variables. Available data are

Step 2: A knowledge base that includes formulation of the fuzzy rule set, based on an expert knowledge

Step 2a: A rule base containing a number of fuzzy 'If–Then' rules;

Step 2b: A database that defines the membership functions of the fuzzy sets used in the fuzzy rules;

Step 3: A decision-making unit that performs the inference operations on the rules; and application of a fuzzy operator to obtain one number representing the premise of each rule,

Step 4: A defuzzification interface that transforms the fuzzy results of the inference into a crisp output.

Step 4a: Shaping of the consequence of the rule by implication,
Step 4b: Defuzzification.

Soft computing method using Artificial Neural Networks (ANN) is motivated by the recognition that the human brain computes in all the different ways from what the digital computer does. Neural network does not have real nerve cells; instead an artificial system of neurons that carry out the computational work. It is representation of complex decision making problem by a neural network system.

Genetic Algorithm (GA) is a natural selection soft computing methodology to choose from such large combination of events with uncertainty. It is an optimization and heuristic search technique that uses techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination). GA works simultaneously on a set (population) of potential solutions (individuals) to the problem. The algorithm starts with a set of solutions (representing chromosomes) called a sub-population. Then candidate solutions or operating conditions are chosen with qualitative or quantitative measure of fitness values. This fitness measure is used to select solutions meet some performance criterion of evaluation and used to select "surviving" individuals that will "reproduce" a new, better sub-population (Huang et al. 2010). Then, the individuals will conduct alterations similar to the natural genetic mutation and crossover. At times, soft computing methods like FL, ANNs, NFS, Evolutionary Computing, Probabilistic Computing, are overlapping and are combined in certain logical order and their combined effect are exhibited in decision making problems.

We first represent all the demand and inflow combinations as demand and supply nodes in the Artificial Neural Network (ANN) with associated fuzzy logic (FL). The default and optimized dynamic reservoir operation simulation results give rise to different fuzzy decisions discussed in the following sub-sections. The default and optimized dynamic reservoir operation simulation results give rise to different fuzzy decisions discussed in the following sub-sections.

4 The Proposed Bi-Level Neuro-Fuzzy System Soft Computing

The main execution of the model involves the following three neural network operation logic that are referred as first comes first served (FCFS), first comes last served (FCLS) and the neural network correction operations (NNCO) that are progressively updated when the algorithm communicates data.

4.1 Feed forward neural network operation

In order to begin irrigation agriculture, sufficient water capable to meet all the irrigation demand for the coming dry season should be stored in the reservoir during the wet season. At the start of the release decision process, reservoir operation simulation sets the allowable release range to the physical limits of the dam or outlet. For transient reservoir operation, we assume the reservoir is first time filling and all the water supply from upstream area will be stored in the reservoir until the water level exceeds the dead storage level (DSL). Throughout the planning horizon, DSL is the lowest point of the range for the storage level. Release decision below this point is not possible to withdraw water for downstream beneficial uses. However, the stored water below DSL is available for in-stream uses like fishery, navigation and recreation.

In this first operation rule FCFS, priority is given to conservation of water for supplemental irrigation and the reservoir is expected to be filled to the brim at the end of wet season. FIFO is "A -Wait -To- See", “FCFS” greedy search heuristic given by equation (4).

$$V^{nt}{}_{j} = V^{nt-1}{}_{j} + d^{nt}{}_{j}{}^{+} - d^{nt}{}_{j}{}^{-} \tag{4}$$

At any time when the water level exceeds the FCL the fuzzy logic operator returns the highest membership degree of 1 for the reservoir storage level and remains so until the first dry season occurs.

However, cases may arise in which the reservoir is not filled to its maximum level at the end of wet period to meet full irrigation demand during dry season. In this operation logic farmers irrigate more water during beginning periods when the reservoir is "full" or the inflow is "high". However, this decision may result in an inefficient solution if the reservoir empties before the end of the dry season as in "drought" areas. Water is important at the initial development and flowering stages more than the late developmental stages. Thus, expertise knowledge plays a significant role to the irrigation planning.

4.2 Feedback response operation

The default operation logic of water conservation (FCFS) contradicts to the flood control objective to some extent because except the overflow beyond the reservoir maximum capacity, “little” water is depleted for flood control operation (FCO) and once the water level reaches the highest fuzzy membership degree of 1 all the incoming excess water beyond canal capacity limit, it overflows.

In "humid" climate or "fairly good" inflow conditions the reservoir may be filled before the end of the flood periods and there is “small” space above FCL to trap any incoming flood peak afterwards, as a consequence, the water overflows above the dam and reservoir outlets and may probably cause flood inundations in downstream stream areas if the probability above FCL is “high”. In this case all the incoming excess water overflows.

${d^{nt}}_j^{+}$ is the overflow volume and the fuzzy logic operator assigns membership degrees between 0 and 1 as “low”, “average” or “high.” Thus, it is necessary to deliberately release water ahead of time so that the overflow at any single period does not exceed some FCL based on a knowledge base on environment protection.

In the second phase of planning, if the reservoir is filled to its maximum limit before the end of the wet season and there is high flood for some wet periods, it becomes necessary to change the default forward operation logic. Thus, it is necessary to deliberately release water ahead of time to environment in downstream at the initial wet periods with the anticipation that more water would be stored before the end of wet periods so that the overflow at any single period does not exceed some FCL. This limit may be accessed from environment protection authority's database.

Mathematically, the total overflow beyond irrigation water demand during all the wet season is distributed to all wet season using any of the convenient bankruptcy rules (Mianabadi et al., 2014). More appropriately, if the input-output operation results in good water conservation goal and yet the reservoir is not empty at the end of the dry season, priority is given to flood control and the reservoir is depleted before the beginning of rainy season to its lowest level in order to trap any incoming flood peak. The operation logic in this case is obtained by a backward recursion dynamic operation (Sari et al., 2016) beginning with the end period of dry season and ending with the first wet period, each time calculating the minimum storage level of the reservoir to meet all the irrigation demands afterwards. This is an intelligent learning neural network given by equation (5).

$${V^{nt-1}}_j = {V^{nt}}_j + {d^{nt}}_j^{-} - {d^{nt}}_j^{+} \qquad (5)$$

4.3 Neural network correction using bankruptcy rules

In both FCFS and FCLS operations the water allocated to periods may be below the normal irrigation demand or the overflow is “high” or “very high” in which cases recourse actions are made by the NNCO. Water deficit at the end of the planning period may occur because of one or more of the following reasons. The water inflow during dry season is “low” or “very low”, the reservoir is not filled to the brim during the previous season, the rainfall event is average or below average, the reservoir evaporation is “high” or “very high”, or the reservoir storage capacity cannot accommodate full irrigation demand etc. All of these expressions are fuzzy descriptions of very complex environment conditions and hydrology factors.

5 Results, Analysis and Discussions

5.1 Case study area

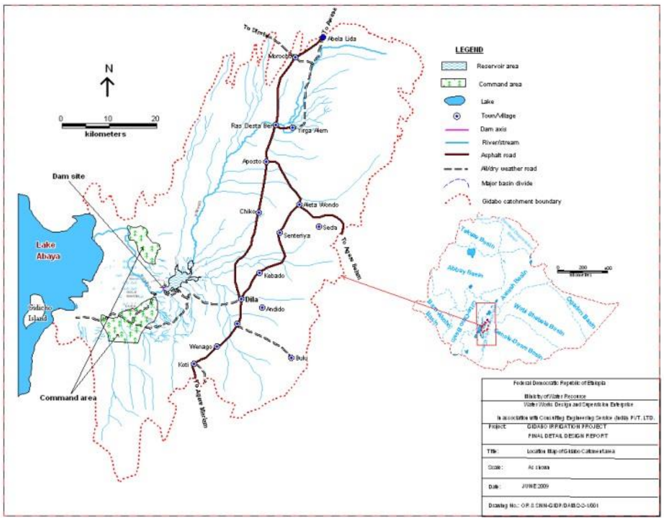

Fig. 1: Location map of Gidabo Dam farm units and reservoir in Gidabo Watershed of Ethiopia

Generally speaking the Gidabo Watershed is a highly important region in Ethiopia comprising of economically and ecologically rich zones from three regional states alongside the main Ethio-Kenyan corridor. It stretches from North East to South West a distance of around 120 km, a catchment area of about 3440 sq. km. The Gidabo Watershed is shared by W. Guji zone of Oromia National Regional State, parts of Sidama National Regional State and Gedeo zone of Southern Nations, Nationalities and People Regional State. It is found in the Abaya-Chamo sub-basin of the Rift Valley Basin in Ethiopia. River Gidabo originates in Sidama

National Regional State. The river is one of the main flow contributors to Lake Abaya (Mechal et al., 2015). The dam was built in the downstream areas.

5.2 Irrigation water demand and supply

Water supply and demand take into account the inflow from an upstream reservoir and catchment area, upstream irrigation water demand, the flow regulation for non-consumptive uses and downstream flood risk management goals based on the pre-designed states of the reservoir size, canal and outlet capacity limits. In irrigation planning, water availability during dry months affects the real-time operation of the reservoir when modifying successive feasibility studies in order to adopt or modify crops to grow, area to irrigate, water to release or store (Tulu, 2003). In the study area, the annual planning cycle has one wet season followed by one dry season.

Two water demand scenarios based on two land use plans of Gidabo Irrigation Dam (GID) project feasibility studies, the first one referring to feasibility study in 2009 to irrigate net area of 7374 ha and the second revised plan in 2011 to irrigate net area of 8164 ha of land by Left Bank Main Canal and 3810 ha of net area by Right Bank Main Canal, summing up to 11,974 ha through its canal distribution networks (MoWIE 2008, 2009, 2011).

For modeling purpose, an irrigation efficiency of 60% is considered as an adaptation measure in place of the irrigation efficiency of 48.6% proposed during feasibility study 1. In all scenarios, in addition to GID there are 527 ha irrigation areas with diversion structure estimated to 2.0 which are operated during dry spell in the year (Oct-March). Furthermore, compulsory downstream release for environmental requirement in feasibility study 1 was considered as 4.76 M m^3 per month (1.84 m^3 /s) which is equal to 10% of annual mean flow distributed equally among all the months. This flow is not directly deducted from the water availability scenarios but it is regulated through the reservoir operation of GID. Thus in the irrigation demand and reservoir operation analysis, this amount is added to the planned irrigation demand in the entire reservoir operation model. However, this may have effect on the active storage size of the reservoir expected to satisfy full irrigation demand.

A new hydrology flow guaging station at Meissa (near the dam site) is set up in 1997 on Main River where its catchment area is 2575 km^2 with mean annual runoff 238.85 mm and mean annual discharge 615.05 M m^3 . The minimum, average and maximum water availability scenarios refer to the corresponding values in the hydrology report for the years 1997-2006 for annual inflow ranges 300<400, 350<450 and 450<600.

Table 1 Input data of monthly inflow and irrigation water demand for GID Reservoir

	[Inflow values (M m^3)]	[Demand values (M m^3)]	Fuzzification
	[Lower, Middle, Upper]	[Lower, Middle, Upper]	Seasons
Dec	[13.8,16.2,31.2]	[27,28.6,40.9]	Dry
Jan	[4.9,5.8,14.4]	[24,34.2,36.1]	Dry
Feb	[0,0.8,8.2]	[11.6,15.9,30.3]	Dry
Mar	[1.8,2.8,8.4]	[6.4,7.3,13.9]	Dry
Apr	[15,29.5,30.6]	[6,6.7,7]	Wet
May	[31.3,56.7,59.4]	[6.5,11.7,16.1]	Wet
Jun	[28.7,32,46.4]	[14.1,14.1,20]	Wet
Jul	[19.8,25.8,57.4]	[12.5,17.2,17.3]	Flood
Aug	[24.4,41.6,63.4]	[8.4,10.6,15.1]	Flood
Sep	[29.9,61.7,70.5]	[9.4,9.6,12.3]	Flood
Oct	[54.9,69.2,71.2]	[11,16.3,23.5]	flood
Nov	[25.1,32.1,44.1]	[20.1,22.8,34]	Dry
Sum	[249.6,374.2,505.2]	[157,195,266.5]	Dry
Mean	[20.8,31.2,42.1]	[13.1,16.3,22.2]	Dry
Maximum	[54.9,69.2,71.2]	[27,34.2,40.9]	Wet
Canal(l/s)	[20.89,26.33,27.09]	[10.27,13.01,15.56]	
m^3/s/ha	[1.49,1.88,1.94]	[0.73,0.93,1.11]	

Table 1 summarizes the monthly inflow and demand given as triangular fuzzy numbers with lower, middle and upper values as inputs of water demand and supply for the proposed BL-NFS reservoir operation model. One can see that the periods January to March are extremely dry and the inflows during these periods are negligible due to the competition of water in upstream areas. The upstream irrigation areas do not have reservoirs but they extract directly from the barrage by diversion structures. This also has direct effect on the reservoir size and operation of the downstream reservoir. In this worst case sensitivity analysis, the input data given in Table 1 shows the inflow during the dry and very dry seasons are "very low" and the irrigation water demands are "high" or "very high". However, the inflow during wet season are "fairly good" because the total excess during this season can compensate the irrigation demand if the reservoir can accommodate the full demand.

We fuzzify a season as "dry" if the upper demand exceeds the lower inflow and their difference is the fuzzy measure of deficit for each dry period. A period is "wet" if the lower inflow exceeds the upper demand and their difference is the fuzzy measure of the wet period excess. A wet period is "floody" if the lower inflow exceeds the flood control limit. Using fuzzy arithmetic the excess and deficit of water during each dry and wet periods are calculated and the ANNs are trained the forward and backward operations and are communicated each other to identify efficient solutions for storage, release and overflow decisions.

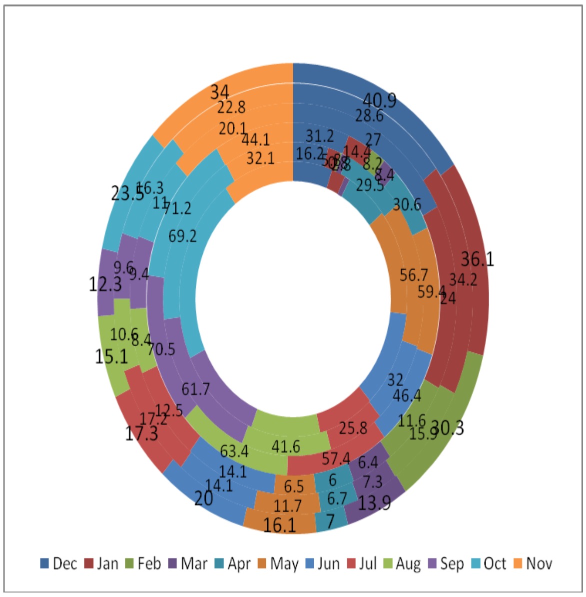

Fig. 2 Demand vs. supply combinations

5.3 Reservoir characteristics

GID is a newly inaugurated multi-purpose irrigation reservoir which has been in operation after 2019. The major crops planned to grow in the command area are cotton, wheat, maize, sesame, tomato, soybean, groundnut and mango. The reservoir has a gross storage capacity of 102 M m^3 , a live storage capacity of 69 M m3 and dead storage capacity of 23 M m^3 .

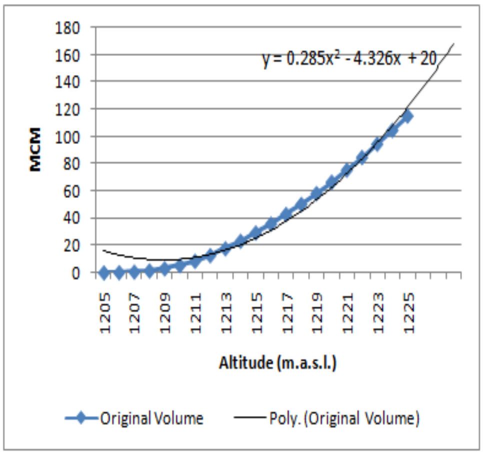

Fig. 3 Quadratic approximations of volume vs. altitude

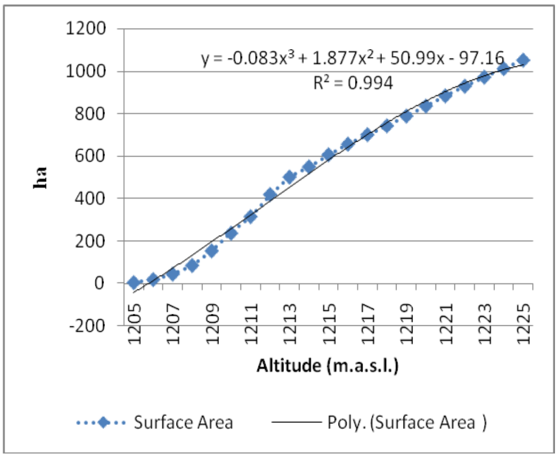

Fig. 4 Polynomial approximation of surface area-altitude

5.4 Reservoir water conservation operation

In simulation, the fuzzy rules are used as follows: Knowing the reservoir inflow, season of the year and the excess/deficit (i.e., high, medium etc.), appropriate fuzzy rule for the period is made as the proportion to store or overflow. The fuzzy operator, implication and aggregation together yield a fuzzy set for the release. A crisp release is then obtained by using the centroid of the fuzzy set. Figures 5-7 show the storage levels of the reservoir after execution of BL-FNS for different demand and supply nodes of the ANN at initial stage of the algorithm execution. The fuzzy rule of the release is obtained by applying the fuzzy rules of whether supplemental irrigation from the reservoir is made. Then the admissible set of storage level of the reservoir for all demand and supply nodes are determined.

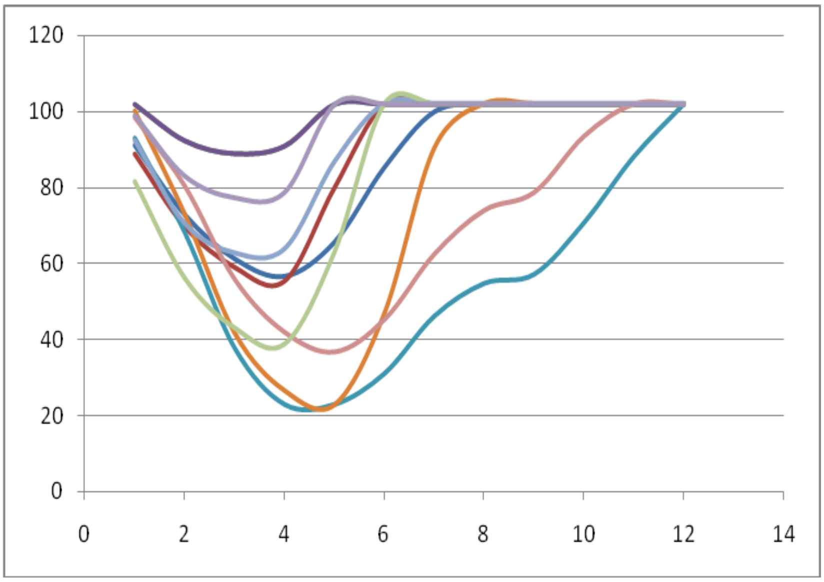

Fig. 5 The ANN responses to reservoir operation under different demand and supply conditions for the forward operation

The interpretation of Fig. 5 is that the forward operation guarantees filling the reservoir before the end of the wet season and all the incoming excess water beyond canal capacity overflows.

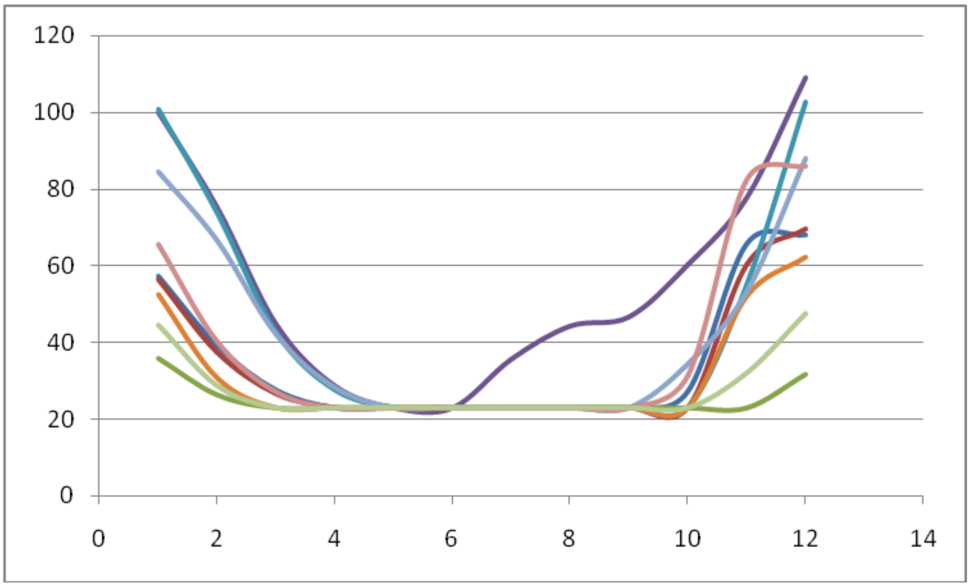

Fig. 6 The ANN reservoir operation under different demand and supply conditions for the backward operation

The interpretation of Fig. 6 is that the backward operation eliminates all the excess storage beyond irrigation demand and the reservoir is empty at the beginning of wet season but this does not guarantee full irrigation demand if the water demand vs. supply condition changes. The forward and backward operations are ideal solutions of the water conservation and flood control operations. As a result, they may be not feasible to the other objective.

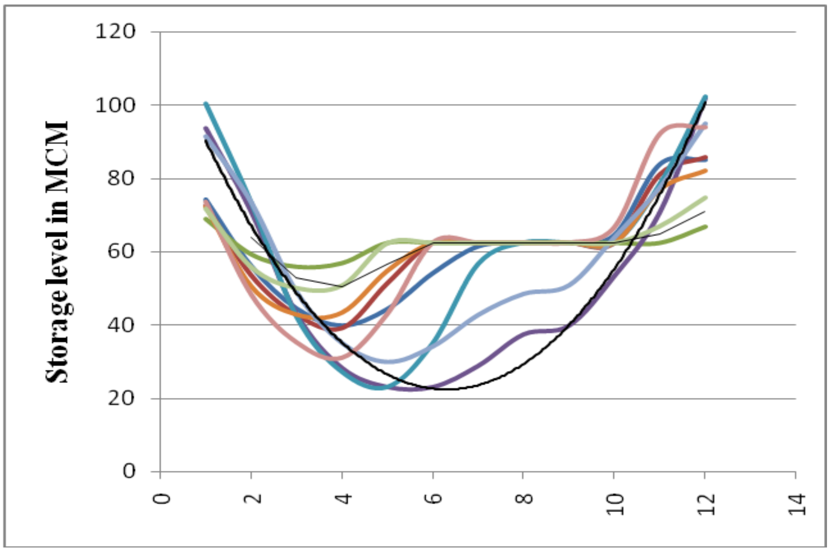

Fig. 7 The ANN responses to reservoir operation under different demand and supply conditions for the communicated operation

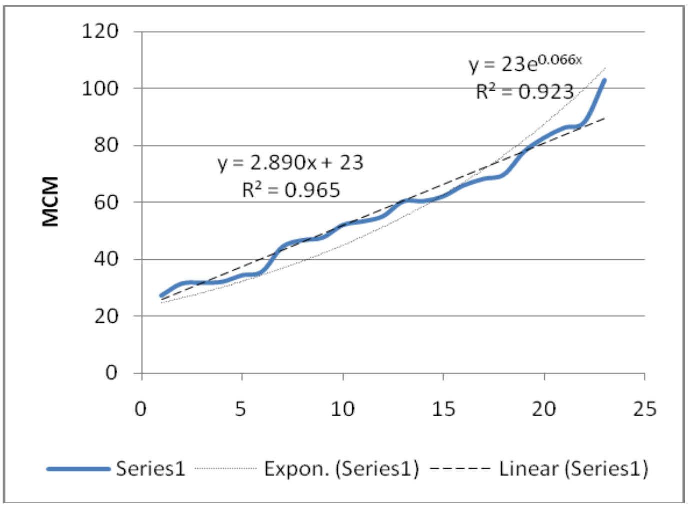

Fig. 8 Continuous time linear and exponential reservoir filling operation during wet season

The interpretation of Fig. 8 is that during the reservoir filling phase beginning with the first wet season, the wet period is partitioned into 3o equal units and the water level is allowed at a rate of 2.89 M m^3 during each sub-units and the rest of inflow is continuously overflows or released for downstream beneficial uses.

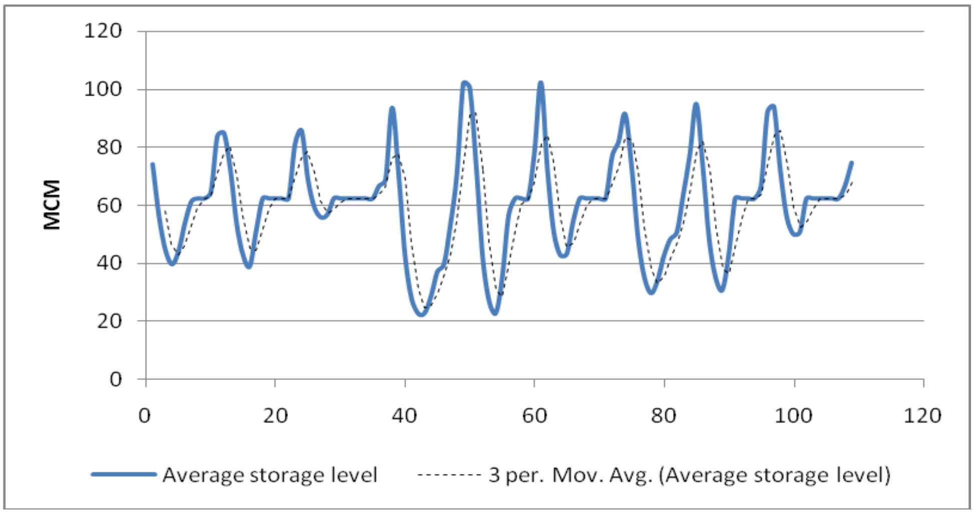

Fig. 9 Average expected reservoir operation policy for ten years time

The interpretation of Fig. 9 is that during the beginning phases of operation the reservoir operates in between the fuzzy storage levels 40 and 80 and gradually increases water conservation. In the second phase the project tries to enter full production capacity without increasing water use efficiency and operates between the two extreme fuzzy storage levels but the penalty terms for both not meeting irrigation demand and expedience of fuzzy flood control limit are high or very high. In the third phase of operation the project enters into full production level but due to the application of bi-level neuro-fuzzy system application, the penalty terms for both not meeting irrigation demand and expedience of fuzzy flood control limit are minimized.

5.4 Reservoir overflow for flood control operation

For the flood control operation, the flood risk is measured (as low, medium or high) and fuzzy decision of deliberate release for downstream non-beneficial uses are made in references to variable flood control limit. The fuzzy rules of storage and overflow are communicated sufficiently by ANN.

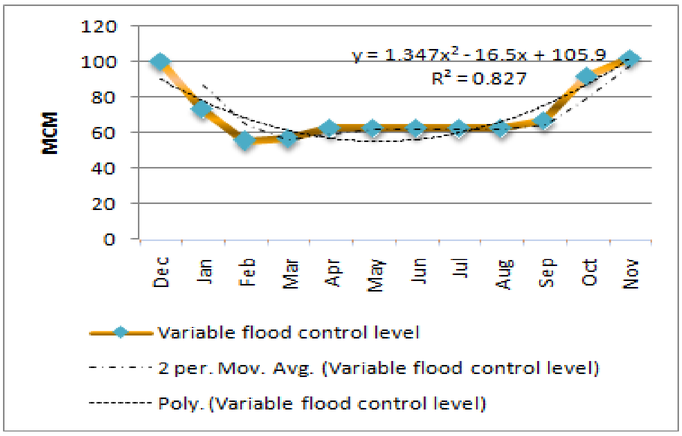

Fig. 10 Variable reservoir flood control limit

The interpretation of Fig. 10 is that at any iteration of the algorithm, if the observed water level is above the variable flood control limit, then more water should be released than incoming. However, if the observed water level is below the variable flood control limit, then more water should be stored than released.

Figures 11-12 show the amount of excess water incoming after execution of BL-FNS for different demand and supply nodes of the ANN. The fuzzy rule of the release is whether to store water or release ahead of time in comparison to the reservoir is made. Then the admissible set of storage level of the reservoir for all demand and supply nodes are determined.

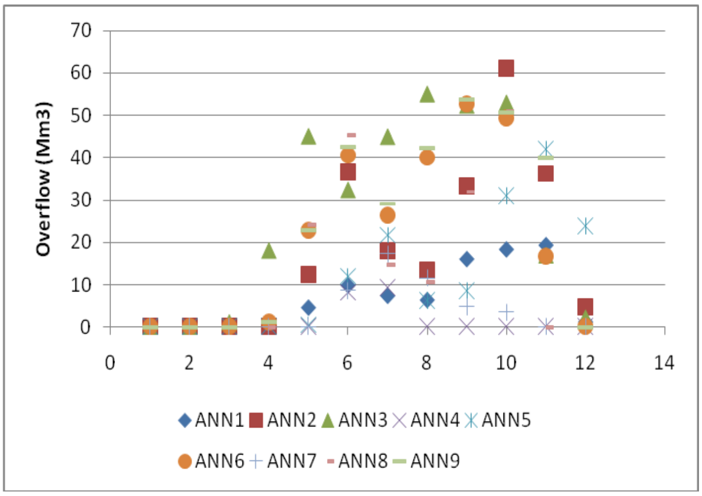

Fig. 11 Reservoir overflows under different demand and supply conditions for the forward operation

The interpretation of Fig. 11 is that during the flood controlling phase, the forward neural network operation produces over flooding at the end. The flood risk can rise up to 50-60 M m^3 per a single period.

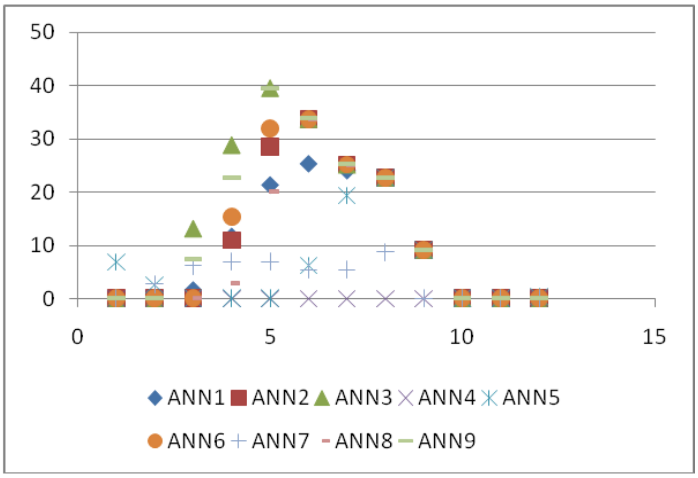

Fig. 12 Optimized reservoir's overflows under different demand and supply conditions for backward operation.

The interpretation of Fig. 12 is that during the flood controlling phase, the backward neural network operation produces over flooding at the beginnings only. The flood risk can reduce to 30-40 M m3 per a single period.

5.5 Reservoir release operation

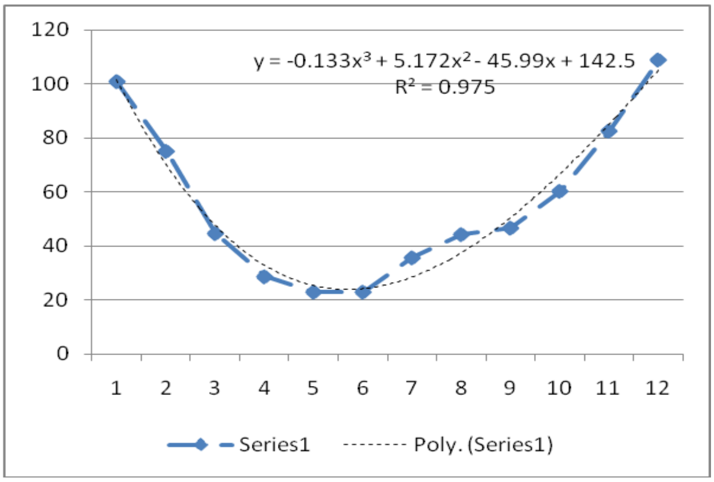

Fig. 13 Reservoir variable active storage level

The interpretation of Fig. 13 is that when the observed storage level of the reservoir is above the variable active storage level, more water is released for consumptive uses in dry season and more water is spilled ahead

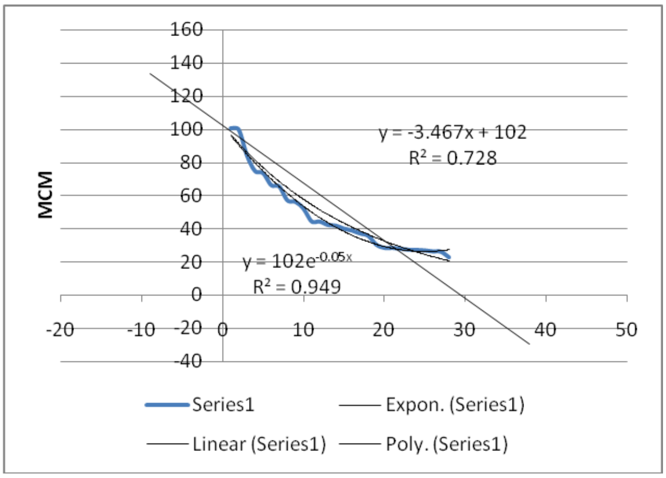

Fig. 14 Continuous time exponential vs. linear decay reservoir release operation during dry season

The interpretation of Fig. 14 is that during the reservoir release phase beginning with the first dry season, the dry period is partitioned into 2o equal units and the water level is allowed to drop exponentially or released for downstream beneficial uses.

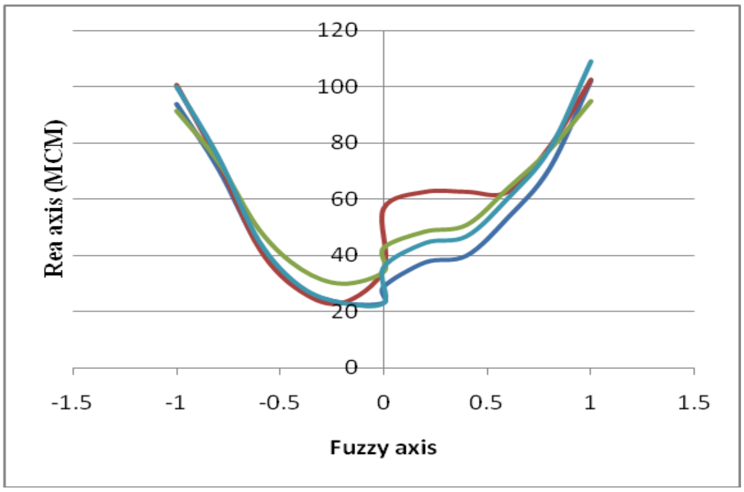

Fig. 15 Fuzzy optimal reservoir operation rule curve

6 Conclusion

In this study an enhanced bi-level soft computing method for optimal reservoir operation model was proposed from available data of inflow and irrigation water demand considering upstream and downstream water demand and socioeconomic data of the study area in Gidabo Watershed from the feasibility studies during planning of the project. The methodology of BL-NFS soft computing using fuzzy logic and artificial neural network representations gives simplified understanding of the complex environment and hydrology events. The worst case sensitivity analysis of upper end fuzzy demand membership and lower end fuzzy inflow membership show that the proposed reservoir size of 102 M m^3 is not sufficient to meet full irrigation demand. On contraries, lower end demand membership and upper end inflow membership show that the reservoir is mainly operated for flood control and the land resources are not fully utilized. In the analysis GID was treated as autonomous/independent of upstream users and the decision of sharing the water deficit during dry periods to all demand and supply nodes, improving the water supply systems in upstream coffee processing plants and irrigation districts help to shift traditional diversion structures to more water saving technologies. The choices were left open to decision makers and researchers.

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