Optimal Reservoir Water Release Policy for The Seasonal Water Yield Reservoir Using Artificial Intelligence

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***Abstract*—The present study focuses on the development of the Conjunctive model for the Pench Irrigation project. As the climate is changing, more and more area is turning into water deficit for irrigation. It's always challenging for the authority to allocate crop area and water resources in such a way that farmers should not be in the loss. Artificial Neuro Fuzzy interface system ANFIS-GA optimization model is used in this for optimization of surface and groundwater (GW) resources in the Pench Irrigation Project. The results show that the command area's GW allotment is significantly reduced, and GW withdrawal may also be limited to recharge in order to preserve the equilibrium between rivers and aquifers. The ANFIS-GA model was subject to continuity, release, and demand constraints. The initial random search of the GA model was carried out with the probability of crossover of 0.80 that of mutation as 0.02, and with a population size of 100 to find the optimal releases. The GA model resulted in an optimized release.**

***Index Terms*—ANFIS, Reservoir Operation, Optimization, Release**

I. INTRODUCTION

Surface water reservoirs have been constructed in many arid and semiarid areas to guard against the unpredictable nature of runoff. However, reservoirs built to combat drought typically provide various functions, such as flood protection, that clash with water availability for irrigation. In addition to resolving the issue of water scarcity, the combined use of surface water and groundwater resources enhances the regional ecosystem of irrigated areas (Azaiez 2002; Cosgrove and Johnson 2005; Cheng et al. 2009; Liu et al. 2013; Seo et al. 2018). Since one source of water may not be consistently available in sufficient quantity or quality to meet the full crop water need over time and space, the concurrent utilisation of surface water and groundwater resources is also essential. In order to mitigate the existing water resource constraints and ecological fragility issues, which are major development-restraining factors in dry regions, increased concurrent use and efficient utilisation of available water resources are required (Garcia-Lopez et al. 2009; Shi et al. 2012). Conjunctive water use has a significant hydrologic-economic function in irrigation and decreases hazards related to erratic surface water supply and their swings (Paydar and Qureshi 2012). Numerous studies have been conducted in order to examine concurrent water use from various angles.

The goal of the model's objective function was to maximise net benefit while taking into account the costs of crop cultivation, water pumping, and overall crop yield over the course of the study. The model's performance was successfully assessed in order to choose the best crop mix and the distribution of surface and groundwater for irrigation. The development of a conjunctive use model for the Pench Irrigation Project is the primary goal of this project. Field research has revealed that although the Pench Irrigation Project's groundwater level is very high, it is not being used. With the aforementioned in mind, a linear conjunctive usage model was created to optimise the net benefit from the available water and land resources.

These models may be primarily separated into simulation and optimization categories. The system operating rules are introduced and detailed in the first one in order to determine the performance level connected to them. On the other hand, optimization chooses a set of decision variable values from the area that is feasible and maximizes or minimizes an objective function (Rani and Moreira, 2010). System operating rules may be included in an optimization process as constraints in the system model description or as part of the objective function (as goals).

Artificial intelligence (AI) is a state-of-the-art technology that resembles the human thinking process in decision making and strategy learning. It has been well recognized for its outstanding ability to handle complex systems (Kurosh 2005, Lin 2000) and has been adopted throughout the technology industry, providing the heavy lifting for logistics, data mining, medical diagnosis and many other areas (Norvig and Intelligence 2002). In the last decade, AI techniques, such as artificial neural networks (ANN), genetic algorithms (GA), and fuzzy theory have also been increasingly applied to tackle some of the issues related to hydrological and water resources systems (Chaves and Kojiri 2007).

Study Area

The Pench River is a tributary of Kanhan River which lies in the Godavari River Basin in India. Pench Irrigation Project as shown in Figure 1 comprises a storage-cum-diversion dam, 23 km downstream of Totladoh Dam on Pench River to impound releases through the tail race discharge after power generation at Totladoh reservoir. It has lined canals on both the banks, envisaging irrigation of 104,476 ha area in Nagpur and Bhandara districts of Maharashtra in India. Left Bank Canal (LBC) has a length of 32.85 km. with full discharge capacity of 90.00 cumec. The LBC has the major irrigation potential of 73,900 ha. Right Bank Canal (RBC) has a length of 48.40 km. with a design discharge of 28.4 cumecs. Water for Naqpur Municipal Corporation (NMC) (190 Mm^3), Koradi Thermal Power Station (67 Mm^3), and Khaparkheda Thermal Power Station (60 Mm^3) are supplied through this canal. As the capacity of the balancing storage of NMC (Gorewada tank) is not sufficient, RBC has to run continuously to feed water for supplies to Nagpur city. RBC has an irrigation potential of 30,576 ha. The temperature in the area rises above 36°C in summer and goes below 20°C in winter. The average annual rainfall is 1,051 mm. Free catchment area between Totladoh and Kamthi Khedi is 388.0 sq. km with an inflow from free catchment of 112.6 MCM. The Kamthi Khedi diversion dam near Parsheoni village has a gross storage capacity of 230.00 MCM resulting in live storage of 180.00 MCM. It is 2,248 m long, with height 44.50 m, above cut-off trench in case of earth dam and 45.5 m in case of masonry dam above the lowest foundation level. The dam comprises of a central spillway with earth dam on right flank and in left saddle. The spillway has 16 gates of size 12 m x 8.

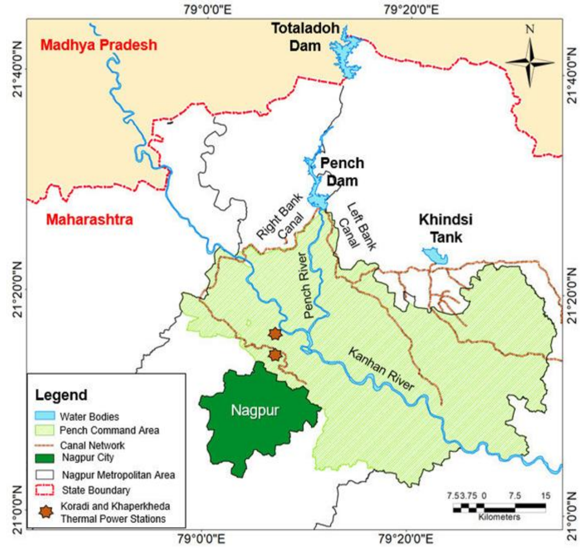

Figure 1. Index map of Pench Irrigation project

II. METHODOLOGY

In this study, the optimization model was connected to the simulation model after the simulation model had already been created. The simulation model, as was already indicated, comprises of two models: a neural network (NN) and a fuzzy inference system (FIS). In the former, an input, hidden, and output layer LMBP neural network was created. Five factors are included in the input layer: groundwater extraction, precipitation, evaporation, distribution of surface water, and groundwater level. The drawdown of the groundwater level is the NN output. Since all of the data are submitted as monthly records, the output will also be produced as monthly figures. The planning horizon is the 2005-2006 water year as a normal, which runs as a typical water year from October of one year to September of the following. The hidden layer of the NN is a 5-30-1 network with 30 neurons. After several iterations of running the network until the maximum correlation coefficient and/or the minimal sum of squared errors are attained, the number of hidden layer neurons is calculated.

The NN model was created and tested independently for each of the three study areas. The performance of the NN was assessed using the criteria R^2 as the Determination Coefficient and as the Validation

Coefficient. All data series were separated into three portions (65% for Training, 25% for Testing, and 10% for Validation). The calculated coefficients are shown in Table 1. These figures indicate a plausible precision in NN's learning and also according to the figures attained for Testing and Training stages, overtraining hasn't occurred.

Table 1. Values of Correlation Coefficient (R) and Determination Coefficient (R2) resulted from NN model

Subarea	Training (R)	Testing (R)	Overall (R)	Overall (R^2)
Pench Irrigation Project	0.80	0.72	0.68	0.69

It is easy to determine the values of the decision variables after choosing a set of parameters for the ANFIS operating model (here created as illustrated in Fig. 3, as its input data is known at the start of each step t. The reservoir mass balance function is defined as follows for continuity of Eq. (1),

$$R_t = S_{t-1} - S_t + I_t \quad (1)$$

where S are the storage levels, R indicates release and I represent inflow for each time t. Although losses are neglected such as evaporation, these losses can be easily incorporated into the mass balance function without compromising the proposed methodology.

If the ANFIS operating model suggests a course of action that might lead to an unfeasible state situation, such as negative storage, certain restrictions might be put in place that compel the reservoir system to maintain the required level. The decisions are then recalculated based on these minimum and maximum values using the inverse of the system state function, such as the reservoir mass balance equation. On the other side, a penalty coefficient may be added if the outcome is physically possible but nevertheless undesirable.

"Optimal target vectors" have been tuned previously using observed values or other optimization approaches to train ANN models in creating an intelligent system. When the reservoir is operated using the ANN operation model, it is anticipated that the optimised parameters (ANN weights and bias) would provide the goal function with the maximum value possible.

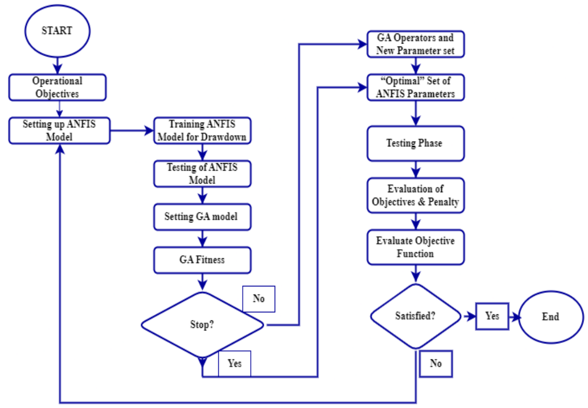

Figure 2 Flow Diagram showing Adopted Methodology for Intelligent Optimum release Policy

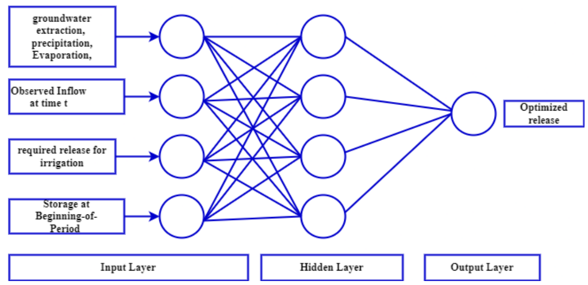

Figure 3 ANFIS Architecture for Release optimization

The final value of the objective function of Eq. (2), considering the whole optimization.

$$F = Max\left[\sum_{t=1}^{T_r} A_t \alpha_t . \delta\right] \quad (2)$$

where at is the assessed objective values for each stage (time step) t; α_t is weight at each time step, we assumed that all weights were equal and equal to 1/Tr. However, other weights may be used, where Tr is the total number of time intervals inside the training operation horizon, to boost the significance of a certain time period or as a discount factor. The objective function (2) will always have a final value between [0, 1] since the total of at in this case equals 1. Last but not least, δ is a penalty coefficient that might be added to enhance the GA training procedure. The suggested Penalty coefficient in this case is defined as in Eq. (3).

$$\delta = \frac{T-P}{T} \quad (3)$$

The aggregated evaluation value, Et, may be defined according to the kind of aggregation operator to be used. The most common aggregation operators are the weighted-average, the product and the minimization. Eq. (4) shows the mathematical formulation of the weighted-average operator, which is the one used later for our case study applications:

$A_t = [\sum_{n=1}^{N} \quad A_n \beta_n.]\ Wheer\ \sum_{n=1}^{N} \quad \beta_n = 1$ (4)

β_n is the weight corresponding to each objective n, N is the total number of objectives. A can be represented by fuzzy membership evaluation functions.

The highest predicted value of the performance function and the total number of generations are the two most often used techniques for the GA training model's stopping criterion. In addition to these two criteria, we have also divided the training dataset into two sets for cross-validation, and we have included a stopping condition for no substantial changes in the objective function after a certain number of generations. For this cross-validation, regardless of a rise in the objective function of the first dataset, the GA training will be terminated anytime a consistent decline in the value of the objective function (OF) of the second dataset is seen. The second criteria is to prevent issues caused by overtraining the ANFIS operating model. Therefore, the GA model is in charge of developing the parameters (in our example, the weights and bias of the ANFIS operating model) based on GA operators until a stopping threshold is achieved. Furthermore, the goal function of the reservoir operation itself, which should be established by reservoir operator authorities, is the basis for the fitness value employed in the GA model in this instance.

After the GA model has determined (optimised) the "optimal" weights, the reservoir is operated across the testing horizon using the ANFIS operation model. The achievement of the operational goals, as determined by the value of the OF, is used to evaluate the operation's success. The procedure restarts with a fresh set of assumptions for the ANFIS model and various evaluation functions if the set of assumptions adopted for the ANN model (such as hidden units and input variables) is not thought to be adequate.

III. RESULTS AND DISCUSSION

As discussed in the previous chapter, operational objectives must be set in order to be able to train the ANFIS operation model without a "optimal target vector". The operational goals described here are connected to the water usage and water rights taken into account in the Reservoir's current operation. The goals have been expressed as fuzzy membership evaluation functions, with a normalised range of 0 to 1, signifying the level of satisfaction at which each goal has been achieved. In our example study, the weighted-average operator is used to combine the values generated for each level of satisfaction. Table 5.1 displays the monthly demand numbers that are utilised for Reservoir's current operation.

Note that the current reservoir operational strategy does not formally mandate the environmental minimum flow as a water use. Some environmentalists, however, believe that it is essential for the survival of aquatic life and healthy environmental conditions downstream of the Reservoir. Therefore, one of our goals also included taking into account the environmental minimum flow. Additionally, because our operation used a 10-day time step (each month is split into three parts, the first 10, the second 10, and the remaining days), flood-related hazards and limits were not taken into account as objectives. However, when using shorter operating time scales, this should be taken into account (e.g., hours to days). We took into account how the Reservoir was now operating to determine the significance (priority) of each objective (as shown in the next sub-section). As a result, several shapes for the fuzzy membership assessment functions were proposed, as illustrated in Fig. 4, because the objectives offer varying importance:

$$A_t = \frac{Q_n}{DQ_n} \quad (5)$$

$$A_t = \left(\frac{Q_n}{DQ_n}\right)^{a_n} \quad (6)$$

$$A_t = 1 - \left(1 - \frac{Q_n}{DQ_n}\right)^{b_n} \quad (7)$$

where A is the evaluation function for each water use n. Q (or W for the variables of the upstream part of the reservoir) is the actual volume of water supplied and DQ is the required demand; a_n and b_n are coefficients used to increase and decrease the priority of each use n, respectively. These coefficients may be adjusted by trial and error considering the results obtained after training and testing of the ANN operation model.

There are two important input variables in this study. The first is the monthly inflow into the reservoir system and, secondly the monthly irrigation. The maximum inflow occurs during the month of October and minimum inflow occurs during the month of April. The monthly coefficient of variation varies from 0.85 to 0.31, the skewness is very high during the month of June and December leading to the complexity in estimating the water availability. Statistical analysis of the historical inflow is given Table 2.

Table 2 Statistical analysis of the historical inflow and Release

Month	Average Inflow (Mm^3)	Average Release (Mm^3)
Jan	0	8.83
Feb	0	15.82
Mar	0	6.15
Apr	0	6.67
May	0	1.92
Jun	22.31	2.66
Jul	29.68	0.20
Aug	24.47	0.26
Sep	68.93	0.40
Oct	0	0.39
Nov	0	0.87
Dec	0	3.67
Annual	145.9	47.84

IV. TARGET STORAGE AND TARGET DEMAND

Based on the needs for irrigation, home use, livestock, small industry, and large industry over the relevant time period, the monthly target release from the reservoir and the target storage are estimated. Table 3 displays the monthly irrigation demand that must be satisfied from the reservoir. The other demand is the constant requirements of municipal demand. The target release is taken as the demand for irrigation, and the target storage is taken as the total of 3 months' worth of other demand requirements plus dead storage. As a result, the reservoir will always have a 3-month reserve for other demands. This aids reservoir operation during times of low inflow.

Calculating how much water needs to be discharged to meet the entire demand is the key goal. Releases should be the decision variable on which the ANFIS-GA is based because the objective function is dependent on the reservoir releases in each time step. Thus, twelve decision-making factors are taken into account.

Table 3 Monthly irrigation demand

Month	Irrigation Area (Hectare)	Irrigation demand Mm^3
Jan	6894	32.45
Feb	6894	17.70
Mar	6894	17.70
Apr	985	17.70
May	985	5.91
Jun	985	20.98
Jul	6598	20.98
Aug	6598	20.98
Sep	6598	4.97
Oct	6598	4.97
Nov	6894	4.97
Dec	6894	4.97
Annual	63817	174.28

It is necessary to build a chromosome with 12 substrings (12 monthly release) totalling 53 binary bits in order to use a ANFIS-GA to solve the reservoir problem. To encode the string in binary, random number generation is used. The objective function is then assessed using these values after the coded string has been decrypted. The evaluation of the fitness function then provides a score for how well the string fits. Following the evaluation of the fitness function, strings are chosen using the Roulette Wheel Method to create the next generation based on their percentage contribution to the population's overall fitness for mating. A thorough sensitivity analysis was conducted in order to choose the ideal population size, ideal crossover probability, and ideal generations.

As an initial search, the system performance (the objective function) is estimated with the probability of crossover of 0.70 and that of mutation as 0.02, with a population size of 25. The system resulted in an average monthly irrigation deficit of 218 and storage deviation of 12220 leading to a total of 12438 and the value is shown in Figure 4.

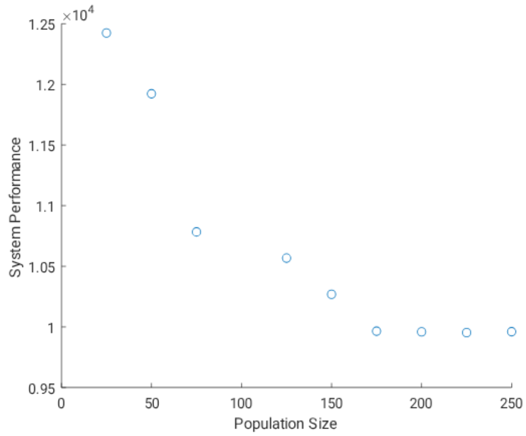

Figure 4. Variation in the system performance with increase in population size.

The system performance for this sensitivity analysis of the probability of crossover is shown in Figure 5. From Figure 5, it is found that the system performance is improving with the increase in probability of cross over.

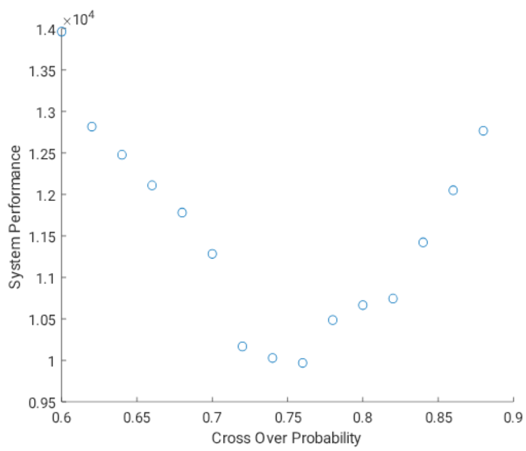

Figure 5. Variation in the systems performance with increase in probability of crossover.

It is found that for 0.6 probability of cross over, the system performance is 13996. It goes on decreasing and attains the minimum value of 9950 for the probability of crossover of 0.76. After this value the system performance decreases with the increase in the probability of crossover, hence the optimal probability of cross over is found as 0.76. The variation of the system performance for this sensitivity analysis is shown in Figure 6. With the variation of the Generation, the system performance increases and it attains a minimum value of 7100 when the population size is 175.

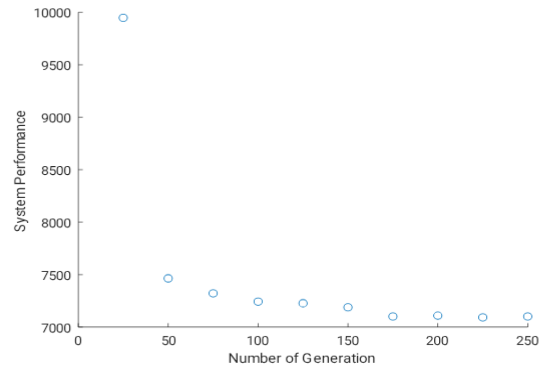

Figure 6. Variation in the system performance with increase in number of generations.

A Comparative plot of actual release, actual demand for an average inflow is given in Figure 6. There is deficit in the release particularly for the months Jan, Feb and Nov. There is excessive release in the months Mar, Apr and May. With the GA generation 175, population of 150, and probability of cross-over of 0.76 the optimised results are shown in Figure 7. From the figure 7 it can be seen that all the demands of months rea satisfied.

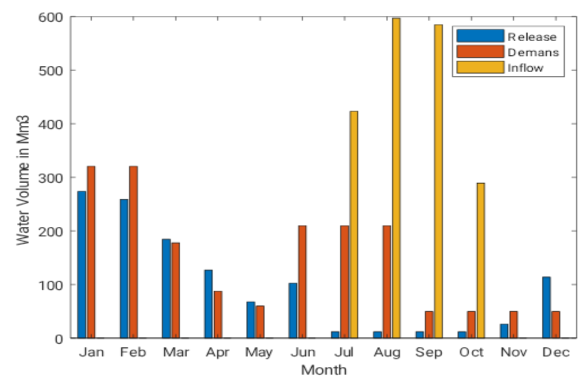

Figure 7. Comparison of actual demand, actual irrigation release and inflow to the reservoir.

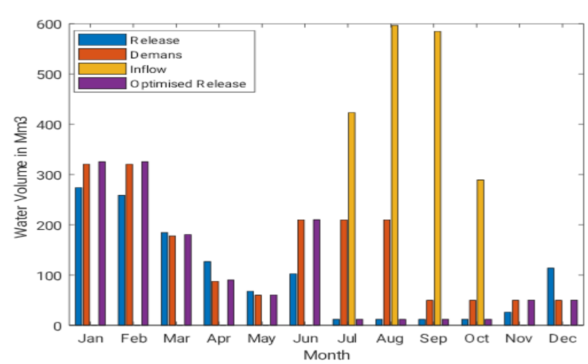

Figure 8. Comparison of actual demand, actual irrigation release and inflow to the reservoir.

V. CONCLUSIONS

A ANFIS-GA model has been developed and applied to derive the optimal operational strategies for the study area under consideration. specifically, a methodology was developed for intelligent systems for reservoir operation. The system is built on the foundation of two widely used artificial intelligence techniques: I ANFIS for building a model for multiple decision-making, and (ii) GA for training (optimising) the ANFIS-based model.

First, a basic scenario with only one decision variable (released water) from the Reservoir was used to design and test the methodology. This demonstrates unequivocally that the ANFIS-GA may offer a sound operational strategy and has a lot of promise for practical usage. The ANFIS operation model's weights were determined by the GA model, which after being tested on a test dataset shown to be very reliable and producing better results.

The objective function of GA model was set to minimize the annual sum of squared deviation of irrigation release and target storage. The ANFIS-GA model was subject to continuity, release and demand constraints. The initial random search of the GA model was carried out with the probability of crossover of 0.70 that of mutation as 0.02, and with a population size of 25 to find the optimal releases. The sensitivity analysis of selecting optimal population, optimal crossover probability and the optimal number of generations, showed a value of 150, 0.76 and 175 respectively for the case study considered herein. The GA model resulted in an irrigation release equal to irrigation requirement.

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