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Optimal Short-term Cascade Reservoirs Operation using Genetic Algorithm

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ABSTRACT

Optimal operation of single and a cascade hydro-electricity reservoirs systems were found using genetic algorithm and excel optimization solver and the results were comparatively analyzed. The objective function was to minimize the difference between actual and installed generation capacity of plants. The state transformation equation (the equation of water balance), the minimum and maximum stage and turbine releases were taken as constraints. A random sequence of ten days has been chosen to run the models. The results showed that the release policy of genetic algorithm was better than that of excel optimization solver in two ways: greater electricity generation and convenience of the operation. The impact of population size, number of trials (runs) and number of generations (iterations) on the optimal solution and computing time in genetic algorithm modeling were presented quantitatively.

Key words: Reservoir operation modeling, genetic algorithm, population size, generalized reduced gradient algorithm

INTRODUCTION

Reservoir management and operations are very complex (Simonovic and Savic, 1989) and requiring careful planning and management strategies. The main reasons are continuous fluctuation of the inflow to the reservoir, periodical demand changes and trade-offs between wide ranges of conflicting objectives (Rani and Moreira, 2010). The focus of planning and management policies is sustainable and optimal use of stored water to meet demand requirements.

Many real-time reservoir operation models have been developed since 1960s. These include linear programming, dynamic programming, nonlinear programming and simulation. The models have been classified on the basis of various methods and algorithms that they have used (Crawley and Dandy, 1993). Operational models broadly classified as descriptive simulation, prescriptive optimization and hybrid models. Descriptive models simulates decisions of reservoir releases on predefined logical rules, prescriptive optimization models uses mathematical programming techniques to solve decision variables and the hybrid models are mainly describe simulation models with piecewise optimization of specific aspect of predefined operating rules (McMahon, 2009).

Several computer models have been developed to design reservoir storage capacity and establishing operational policies during preconstruction planning of new projects, to reassess the existing operation policies of reservoir systems and to support release decisions during real-time operation (Wurbs, 1993). Reservoir optimization problems are challenging since it is dynamic, potentially nonlinear and nonconvex (Labadie, 2004).

Genetic Algorithm (GA) is one of modern optimization methods and the principle is based on Darwinian Theory of evolutionary process. In search for optimal values, three heuristic processes including reproduction, crossover and mutation are applied probabilistically (Labadie, 2004). The advantage of GA is the greater probability to find global extremum point (Li *et al.*, 2008). Excel Optimization solver (EOS) integrated with Microsoft Excel is also used to solve optimization problems. EOS uses Generalized Reduced Gradient (GRG) algorithm. Objective function and constraints are written in different cells. The model requires the adjustment of run-time, iteration, precision and the type of problem (linear, nonlinear, etc.). It also needs information about the target cell, changing cells and constraints. The solver requires only one trial (run).

The concept of optimization is based on safe and efficient use of scare resources. In this case, the water stored in the reservoir is a scare resource. Continued research is needed to investigate efficient and rational use of the water stored in the system. Researchers tried to optimize reservoir operation using different approaches. Zahraie and Karamouz (2004) applied a time decomposition approach to model the operation of two parallel reservoirs. The model was divided in to three different time periods; long-term (monthly), mid-term (daily) and short-term (hourly). The long and mid-terms of operations have been modeled by stochastic dynamic programming, while short-term by deterministic dynamic programming. Shiau (2009) applied hedging rules using multi-objective Genetic Algorithm (GA) to optimize a reservoir operation. The rule mainly depends on three parameters; the Starting Water Availability (SWA), ending Water Availability (EWA) and Hedging Factor ratio (HF). When the availability of water exceeds EWA, hedging is not implemented, where as water availability falls below SWA no additional hedging being enforced. Jalali *et al.* (2006) used improved Ant colony optimization algorithm to model reservoir operation. The model was applied on a finite time horizon and predetermined optimality criterion.

According to Mathur and Nikam (2009), researchers still search the best reservoir optimization model. Mousavi *et al.* (2005) tested three levels of Dynamic Programming Fuzzy Rule-Based (DPFRB) model, including DP model, FRB model and simulation model. It was found that DPFRB model performed well in terms of satisfying the system target performance and computational requirements. McMahon and Farmer (2009) suggest that rule-based storage accounting was well suited for adaptive management policies. The approach has given emphasis on fairness and sustainable reallocation of water. Cheng *et al.* (2008) mentioned that GA model has been widely applicable in water resources system optimization. Mathur and Nikam (2009) stated GA gives better result, but it requires careful selection of parameters. Azamathulla *et al.* (2008) compared Linear Programming (LR) and GA model to maximize irrigation reservoir operation. In the case of real-time reservoir operation, Azamathulla *et al.* (2008) suggested that GA model is superior on linear programming model.

One of the most important parameters of GA is population size. In water resources optimization problems, a population size of 64-300 even up to 1000 has been proposed (McMahon and Farmer, 2009). Running speed and the availability of data are important issues in model selection. Hormwichian *et al.* (2009) proved that Conditional Genetic Algorithms (CGA) model was faster than the traditional GA model. In the case of limited data (Bai and Tamjis, 2007) showed fuzzy logic model is advantageous.

MATERIALS AND METHODS

Hydrological and metrological data of Gumara irrigation reservoir, Ethiopia has been taken (MoWRs, 2008). Averages of 44 years (1961-2004) of data were used for analysis. The data

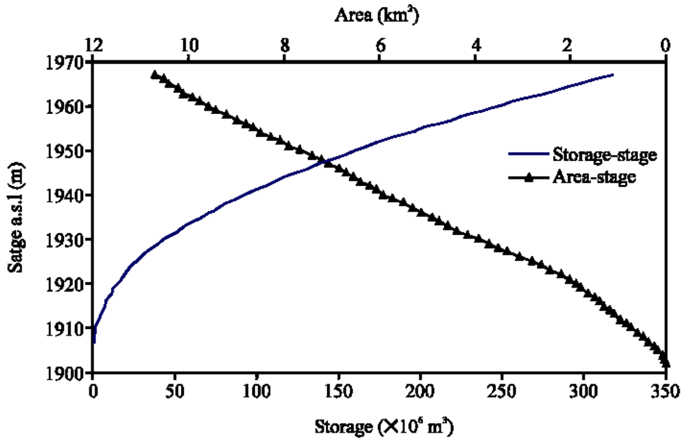

Fig. 1: Storage-Stage-Area (SSA) relationships (Gumara Reservoir, Ethiopia)

included reservoir storage volume, stage, water surface area, river inflow, average rainfall and evaporation. Hypothetically the reservoir used for hydropower generation. Figure 1 shows the Storage-Stage-Area (SSA) relationship of Gumara reservoir. Prior to the establishment of the objective function and constraints, the water balance of the entire system was evaluated. Reservoir operation has been evaluated by the principle of water balance and rule concept (Hormwichian *et al*., 2009). Analysis was made on a single and a cascade of three reservoirs. The cascade reservoirs are arranged as R-1, R-2 and R-3 from upstream to downstream respectively. The assumption has been all reservoirs have similar SSA relationships. In both cases, the study was based on information about firm and installed electric generation capacity of the plants, the requirement of electricity, the preceding and succeeding storage capacities of reservoirs, extreme values of stage and turbine release.

Of the various optimization methods, GA and EOS have been used. The objective function was to minimize the difference between the installed and the actual generation capacity of the plants. The state transforms equation, the daily extreme values of stage and turbine release have been taken as constraints. Figure 2 shows the flowchart to determine optimal parameters using GA. Optimal size of the population, an appropriate number of runs (trials) and relative run-time taken have been studied in both single and a cascade three reservoirs operation. Analyses performed on a daily basis and a random of ten consecutive days was selected. According to the release policy, the entire period of analysis was divided into two groups; weekend (Friday to Sunday) and the other four days of a week. The class was made on the basis of daily power requirements and water availability in the reservoirs.

RESULTS

In GA, the number of run per each population size affects the optimal value. Figure 3 shows the relationship between number of runs and fitness value. In all cases, the value of fitness was best when the number of runs increases. The improvement of the best fitness value becomes insignificant beyond a certain number of runs. The minimum number of runs to achieve the optimum decreases linearly with the population size. This was shown for the example cascade reservoirs by a border line of runs.

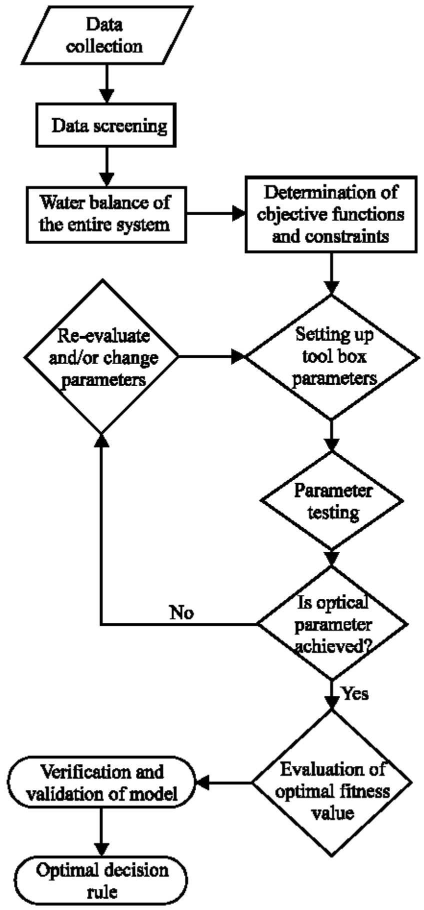

Fig. 2: Analysis flowchart using GA

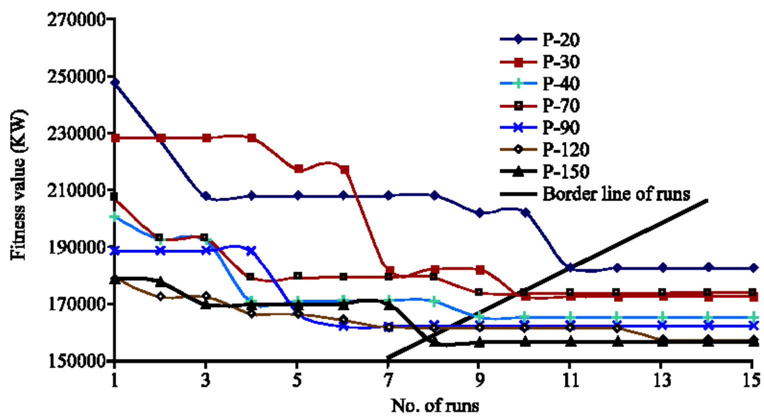

Fig. 3: Optimal GA runs for various population sizes (P)

A reasonable minimum number of runs for all population size were taken as 10. Therefore, the optimum was recorded for 1, 2, 3... 10 runs for each population size for both single and cascade systems.

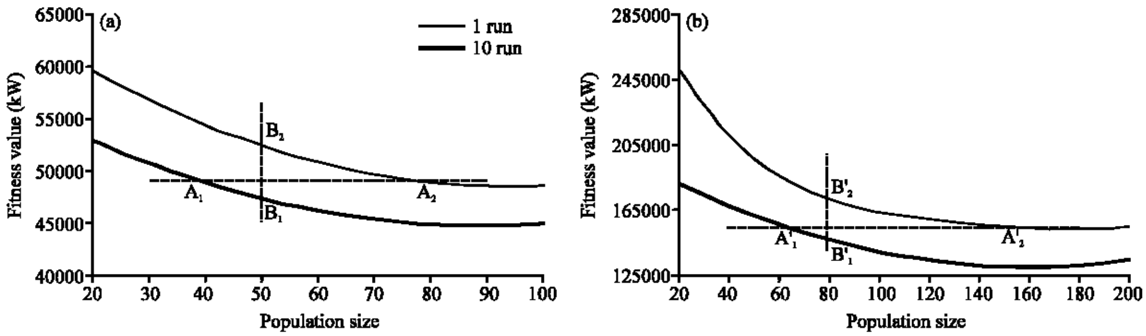

Fig. 4: Optimal population size for (a) single and (b) cascade reservoirs system

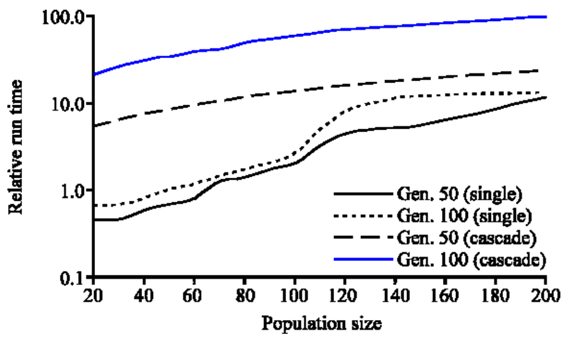

Fig. 5: Relative run-time for generations of 50 (Gen. 50) and 100 (Gen. 100)

To compare the impact of population size and number of runs, sample horizontal (A_1A_2 and $A'_1A'_2$) vertical (B_1B_2 and $B'_1B'_2$) dashed lines were drawn in Fig. 4a and b. As for the horizontal lines it was seen that in the single reservoir case, the fitness value obtained from population size of 80 with only one run could achieved by 10 runs if the population size was 40. The same was true for the cascade case considering population sizes of 150 and 60. As for the vertical lines it was seen that in the single reservoir case, the fitness value obtained from population size of 50 with only one run can be achieved by 10 runs if the population size was 25. The same was true for the cascade case considering population sizes of 80 and 40.

Figure 5 presents an indication of the computer time needed for optimization with various population sizes and generations. Taken the time required for cascade case, population size of 200 and generations (iterations) of 100 as hundred, the other times were shown as percentages (ratios) smaller than 100. For example, with a constant population size of 150, the Run Time Ratio (RTR) for Single Reservoir (SR) with Generation (GN) of 50 was 6, RTR for SR and GN of 100 was 12, RTR for Cascade Reservoir (CR) with GN of 50 was 19 and RTR for CR and GN of 100 was 80. It can be seen that by doubling the number of iterations, the computation time required for cascade case quadruples regardless of the population size. The figure also shows that the relative run-time increased significantly in the case of cascade reservoirs compared to single reservoir. The time needed for the cascade case could get more than 20 times longer than that for the single case with the population size of 100.

The results of a single reservoir operation using both models were shown in Fig. 6. It shows that for the first seven days, GA had a higher release compared to EOS. After the seventh day, results

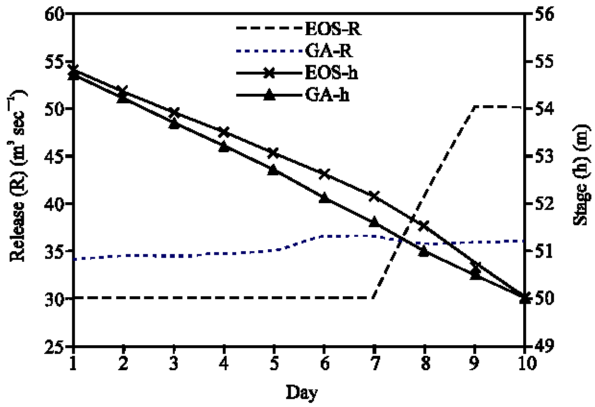

Fig. 6: Optimal release, R and Stage, h for single reservoir system

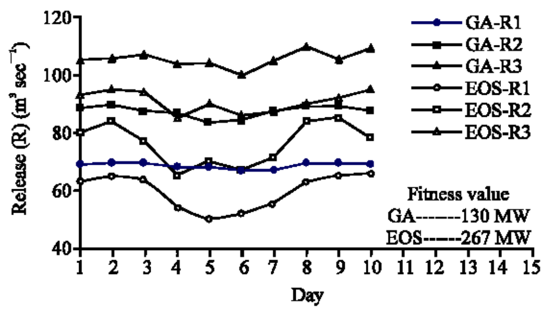

Fig. 7: Optimal release, R for three cascade reservoirs system

had shown an abrupt change in release of EOS. The lower release in the first 7 days with EOS led to an overall larger stage. The larger stage, implies a larger storage, has been in the last three days through larger release. The fitness values of both models were the same.

Optimal operation of a three cascade reservoirs were shown in Fig. 7. Like in Fig. 6, the same practical advantage of GA over EOS, namely a fairly uniform release, can be observed. The second advantage of GA over EOS was a greater total electricity generation, 130 MW<267 MW. This, of course, comes at the price of continuously larger release and smaller storage. While the first makes operation of the station and the structures easier, the second brings about a clear economic benefit.

DISCUSSION

Population size affects the model running speed and optimal fitness value. The lower population size had the faster speed and vice versa. Above a certain value, increasing the size of population gave a small change in the fitness value. Figure 4 a and b show the bands within which the respective optimums lay. The following observations can be made:

- Except for the low population size of 20, the width of the band was fairly uniform and independent from the population size for both single and cascade systems
- The best fitness value was improved with increase of the number of runs. The same was the case with the increase of the population size up to a certain limit. The limit could vary from a

situation to another. For example, population sizes of 80 and 150 gave the optimum for single and cascade reservoir systems, respectively using 100 generation. Wardlaw and Sharif (1999) found for the four-reservoir problem, global optimum was achieved within 500 generations with a population of 100

The uniformity of the release with GA brings about a more convenient operation compared to the fairly sudden changes with EOS. Rapid changes in release may entail difficulties in terms of operation management, damages to the hydraulic structures (gates, valves...) and rapid downstream water changes and river flooding and erosion. This difference in the rates of release was significant in practical sense only. Theoretically, it should be recognized that no constraints have been introduced for the rate of changes in release. Ahmed and Sarma (2005) also suggests that operating policy derived by GA was promising and competitive and can be efficiently used for deriving operating policy for a multipurpose reservoir.

In the case reservoir operation, Azamathulla *et al.* (2008) suggested that GA model is superior on Linear Programming (LP) model, (Kumar *et al.*, 2006) found that the optimal operating policy obtained using the GA was similar to that obtained by LP, (Jothiprakash and Shanthi, 2009) suggested GA model performed better than dynamic programming model. This research also proved that GA is advantages than EOS in the case of release uniformity and electric generation.

CONCLUSIONS

Using storage-area data of an Ethiopian dam reservoir, the optimal operation of two hypothetical electricity generation stations are taken as examples to test the performance of genetic algorithm in search for optimal operation of two scenarios: single reservoir and a cascade of three reservoirs. The duration of electricity generation was taken as 10 consecutive days and three types of constraints were imposed: state transformation (water balance), minimum and maximum turbine releases and recommended minimum and maximum stages. Varying population sizes in GA, number of trials (runs) and generation (iteration) the performance of GA was compared to that of Generalized Reduced Gradient Algorithm (used in Excel Optimization Solver (EOS)). In the context of short-term (10 days) reservoir operation, the following conclusions were made:

- GA gives a better release policy in both single and cascade reservoir cases in terms of release uniformity and electricity production
- For each population size selected in GA there is a minimum number of trials (runs) with which the optimal can be achieved. A 'border line of runs' was introduced to guide towards such number
- For both single and cascade reservoir systems, there is a maximum population size beyond which little improvement in the solution can be achieved. 80 and 150 population sizes provide for rough guides for single and cascade cases, respectively
- A preliminary guide for the impact of population size and number of generation (iteration) on the computer optimization time is given

Among the next steps of this ongoing research is the comparative study of long-term optimal reservoir operation covering durations up to one year.

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