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Dam and Reservoir System Management based on Genetic Algorithms

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ABSTRACT

Indeed, there are many hydrology variables influence on the operating of dam and reservoir system. Thus, modelling of dam operation is a complicated issue due to the nonlinearity of such hydrological parameters. Hence, the identification of a modern model with a high capacity to cope with the operation of the dam is extremely important. The current research introduced good an optimization algorithm, namely Genetic Algorithm (GA) to find best operation rules. The main aim of the suggested algorithm is to minimize the difference between irrigation demand and water release value. The developed algorithm was applied to find operation rules for Timah Tasoh Dam, Malaysia. This research used significant evaluation indexes to examine the algorithms' performance. The results indicated that the GA method achieved low Vulnerability, high Resilience and Reliability. It has been demonstrated that the GA method will be a promising tool in dealing with the problem of dam operation.

1. Introduction

Determining best operating policies for dam and reservoir system is critical to managing water resources. An optimal operation for dams achieves the correct utilize of stored water to meet various water requirements. Constraints on the amount of water, whether in excess or deficient, are fueling interest in developing several robust methods to deal these constraints [1–5]. The reservoir operating system is, in fact, a complicated, non-linear, multi-constraint, multi-purpose system [6]. In order to provide the best answer to the reservoir operation problem, mathematical programming approaches, including optimization algorithms, have been widely applied. These algorithms serve as the operating principles for determining how much water should be discharged from the reservoir at different times [7].

In recent years, the popular method called Stochastic Dynamic Programming (SDP) was utilized in solving the operating problem by [8,9]. The developed optimization method was applied with consideration ensemble reservoir inflow forecasting. The SSDP method was also used by [8] to present successful reservoir operation policies. The authors combined the proposed method with predicting group flow. Th research work has shown that the prediction accuracy can lead to a significant impact in improving the operation of the dam reservoir [5,8].

Another optimization algorithm is Particle Swarm Optimization (PSO) where it has been explored to deal with the reservoir operation problem [10–12]. The genetic algorithm is a common technique in implementing optimal policies for a reservoir system. Indeed, several previous studies used the GA method to search for the optimal amount of water release from the dam reservoir like [13–16].

In 2016, [17] combined model for optimal scheduling of the multi crop irrigation demand.

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They have improved the artificial bee colony algorithm by combining differential evolution method with Practical Swarm Optimization (PSO) method to find the best solution to the optimum dam operation problem. On the other hand, Honey Mating Optimization Algorithm (HMOA) has been employed to find operation rules for the single reservoir to attain a minimum deficit between water release and demand [1]. Comparison has been done between the performance of the suggested method with the genetic algorithm. The present research found that the proposed method achieved good results in dealing with the operation of the reservoir with high efficiency [1].

Recently, evolutionary computing techniques have become popular in optimizing reservoir operation and managing water resources [18–21].

2. Case Study

It is vital to investigate the optimization strategies' ability to handle complex situations. The inflow's significant unpredictability and non-linearity make optimal reservoir operation even more difficult. The present research considers the Timah Tasoh Dam (TTD) as a case study for the application of the suggested algorithms. The case study is located in Malaysia, tropical environmental region [22].

Construction of TTD began in 1992 and the dam reservoir began operating in 1995. Timah Tasoh Dam was built to meet multiple purposes such as demand for irrigation water, industrial and domestic uses for Perlis district, Malaysia [23]. Moreover, the dam protects the region against flooding by collecting and holding waters when they reach to certain level. The dam reservoir has a maximum capacity of around 40 million cubic meters (MCM) and a reservoir area of roughly 191 square kilometers (km^2). The water pouring into the reservoir is supplied by two major rivers, the Tasoh and Perlarit rivers.

Monthly flow records for period between 1996 to 2011 have been adopted as input data for developing the proposed methodology [24]. The irrigation water demand and flow values for 12 years are showed in Figure (1). United State Geological (USGS) proposes classifying flows into three categories which are high, medium and low upon on the percentage distribution of the flows.

The percentage greater than 75% is considered a high flow category, whereas the percentage flow distribution between 25% to 75% is a medium class. The low inflow category is the percentage data that is less than 25%. Table 1 presents these flow classes and evaporation losses from the dam reservoir. The evaporation losses are calculated using equation (1 and 2).

$$Evaporation = evaporation\ rate * surface\ area \tag{1}$$

$$Surface\ area = 0.002S^2 + 0.3446S + 2.6553 \tag{2}$$

Table 1. Categories of the reservoir flow and the evaporation values for Timah Tasoh case study[25].

Months	High (MCM)	Medium (MCM)	Low (MCM)	Evaporation (m)
September	15	6	3	0.09
October	29	15	6	0.08
November	41	19	7	0.08
December	27	13	4	0.08
January	10	4	2	0.115
February	4	2	1	0.13
March	7	4	2	0.14
April	10	4	2	0.12
May	9	3	2	0.1
June	8	3	2	0.09
July	12	6	1	0.09
August	15	7	3	0.09

In fact, the demand for irrigation water in the Perlis district represents more than 70% of the total demand. Figure (1b) illustrates the amount of irrigation water demand. It could be noticeable that the surrounding area needs high irrigation water during the months of September, October and November as compared to other months due to the planting season. During the months of January and February, there is no water demand because there are no planting operations. In current research, a reservoir is divided to 10 stages depending on the maximum value (40 MCM) and minimum storge value (27.84 MCM).

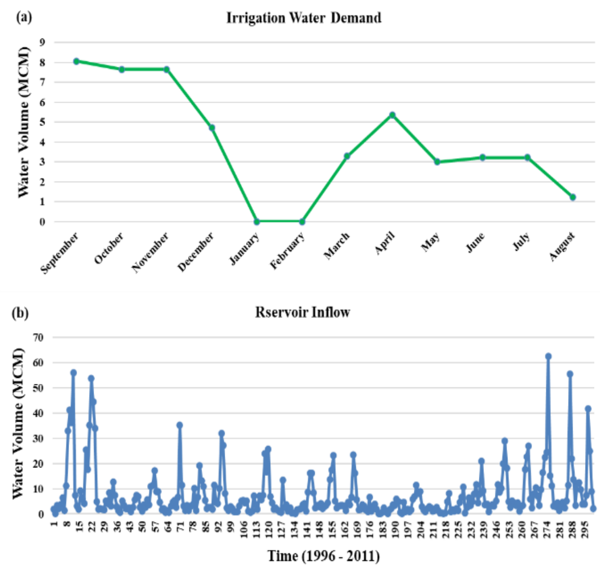

Figure 1. (a) Irrigation water demand volume for each month, (b) Reservoir inflow data for the period between 1996 to 2011.

3. Methodology

3.1. Genetic Algorithm (GA)

The chromosome sequence in the Genetic Algorithm (GA) should be used to encode the problem parameters. Possible solutions to the optimization problem are represented by such chromosomes. In the first stage of the often-random search process, the chromosome's initial populations are created. The population varies depending on the situation, but it frequently encompasses hundreds or thousands of potential solutions [26–28]. The search space should be covered by all possible solutions. The offspring's parents are represented by the populations, which are generated through three stages: selection, crossover, and mutation. The offspring becomes the following generation's parent, and the process repeats itself in the search space until the problem is solved optimally.

The suggested algorithm simulates the principles of natural selection. Based on these principles, the best solutions can be selected, and their superior features passed on to their offspring. The next generation's progeny is predicted to outperform their parents. Many future generations will be able to produce adequate answers, and the best option will be picked as the optimal policy for the reservoir operation problem. Many previous studies have used the capacity of the Genetic Algorithm to address the optimization problem for the operation of water resources systems, according to the capabilities of the GA approach (e.g. [29–32]).

3.2. Performance Indicators

After receiving a model's outcome, the suggested model's success is assessed using a variety of metrics. For checking the accuracy level of the introduced approaches, four performance indicators are used. Short index, reliability, resilience, and vulnerability are these indices [34]. The most important indicator in determining the model's efficiency in terms of attaining the system's objective function is its reliability.

4. Results and Discussion

Genetic Algorithm was used to find the best operational rules. Such algorithm tries to close the volume gap between irrigation water release and demand as much as feasible. Five input classifications, High inflow, Medium inflow and Low inflow, are used to determine the best rules for operating the reservoir system. Figure 2 depicts the best water release graphs for high flow category with a variety of initial reservoir storages. The research took each month's irrigation water demand into account, except in January and February where the irrigation water demand is zero in these months. However, Figure 2 present only the critical months (i.e., September, October, November and April) in which water demand is high to show the performance of the proposed algorithm with critical situations. When comparing the performance of the offered model during these months, it was discovered that the GA technique matches irrigation water demand in all months with high accuracy.

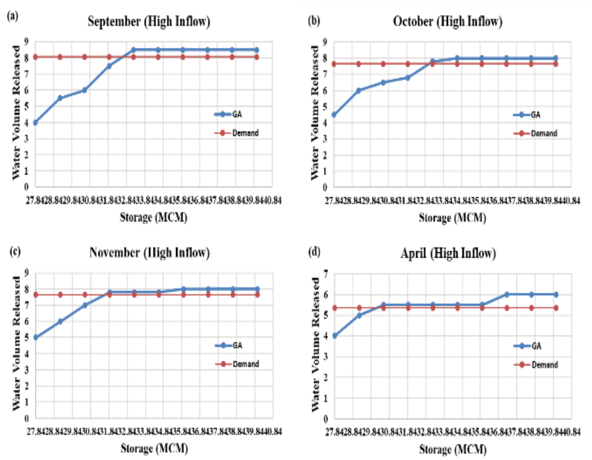

Figure 2. The best operation rules for reservoir system within September, October, November and April with high inflow class

Figure 3 shows the best policies for operating the reservoir system in the event of a medium inflow type. It could be shown that the efficiency of the available strategies in meeting water demand fluctuates substantially from month to month. Figure 1a shows that the maximum irrigation water requirement was in September (8 MCM). As a result, after the fourth step of reservoir storage, the water release obtained utilizing GA techniques clearly meets the water demand. Another notable feature is that the GA policies in October meet the irrigation water demand early with minimal reservoir reserve. The accuracy of GA in establishing optimal reservoir policies is very well, as shown in Figure 3.

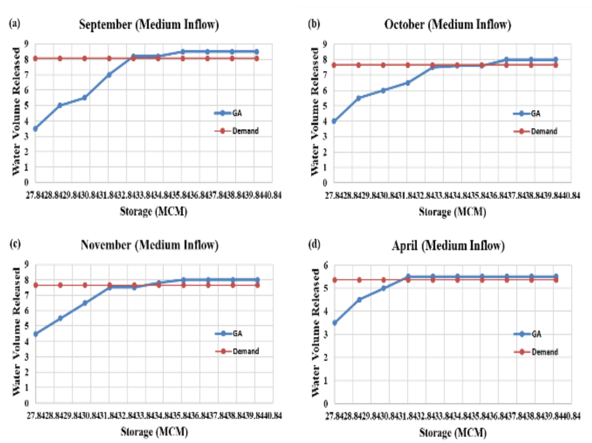

Figure 3. The best operation rules for reservoir system within September, October, November and April with medium inflow class.

The performance of the suggested approach for operating the reservoir system under low inflow conditions is shown in Figure 4. The findings revealed that the Genetic Algorithm ability to supply water demand while lower initial storage is limited. In fact, September is the month with the highest water demand. As a result, determining reservoir policies capable of meeting water demand during this month with minimal initial storage is critical. The GA approach was able to discover the best solution to satisfy the water demand in September with reduced reservoir storage.

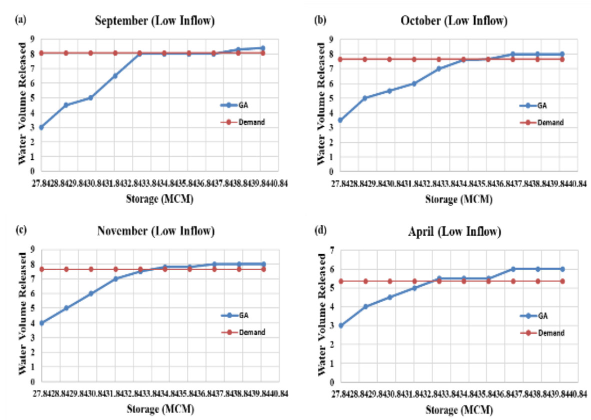

Figure 4. The best operation rules for reservoir system within September, October, November and April with low inflow class.

Figure 5 shows the six-year simulation results using the optimization strategies' release curves obtained by GA method. It should be mentioned that the proposed algorithm (GA) provided acceptable performance in meeting the water demand for the majority of the months. Clearly, the GA algorithm is capable of satisfying medium and low water demands, but its ability to handle high-water demands is limited in some times. With other months, the GA approach has a high level of accuracy in detecting the water demand. The algorithm's capacity to determine the best answer through a search process is demonstrated by GA's precise performance in satisfying demand. This is because the GA approach was successful in locating the global optima within the search space.

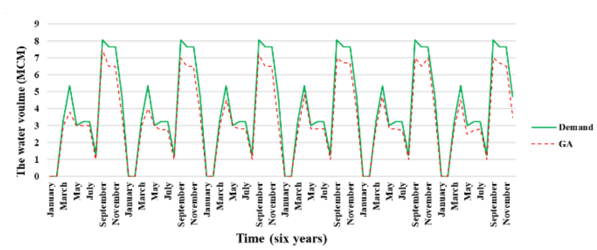

Figure 5. Operation of the reservoir during 6 years utilizing the operational rules obtained by GA algorithm.

Four performance criteria were computed based on the operation period for each approach to analyze the performance of the suggested model, as shown in Table 2. The policy derived from the GA model for operating the reservoir system proved to be more reliable and resilient. Meanwhile, the optimization model must be examined in terms of the failure volume in reaching the aim using the vulnerability index. The results show that the GA technique has less vulnerability than other approaches.

Table 2. Performance criteria magnitude for evaluating the capacity of the suggested algorithm whiling operating period.

Algorithm	Reliability	Resilience	Vulnerability	Deficit
GA	0.87%	36%	33% of water demand	0.28 MCM

The average deficit volume over ten years is the fourth performance indicator in Table 2. It has been noticed that the average deficit volume calculated using GA operational guidelines is acceptable volume. In fact, using the GA model reduces the risks connected with the release choice, hence avoiding the anticipated operation risks associated with reservoir collapse.

5. Conclusion

To determine the best approach for managing the reservoir system, the optimization algorithm was developed: Genetic Algorithm (GA). The goal of the proposed algorithm is to achieve the smallest water deficit volume between irrigation demand and water discharge. The performance of the proposed model was assessed using a variety of statistical measures. The statistical indicator values were calculated for a 6-year period while the reservoir system was operational. It was shown that the Genetic Algorithm (GA) was successful in satisfying water demand during wet and dry seasons.

The results, on the other hand, imply that the GA optimization approach is willing to sacrifice water volume to meet demand during distinct seasons in order to avoid a large water deficit during reservoir operation. Meanwhile, the suggested model GA includes strategies for creating balancing cases in response to various water demand scenarios. In reality, the GA model simulates all of the risks connected with the release decision, with a focus on minimizing the gap between supply and demand. The GA strategy takes into account predicted operational risks, which helps to alleviate concerns about reservoir collapse.

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