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Flood Duration Optimal Operation Of Reservoir Using Moth Flame Optimization

Priya Chauhan[1]* and Sandeep Narulkar[1]

[1]Shri G. S. Institute of Technology and Science, Department of Civil Engineering, Indore, Madhya Pradesh, India.

Abstract: In India, reservoirs are not only used for irrigation and electricity generation; they also play a critical role in flood prevention. During floods, water is stored, kept, and released from reservoirs for a variety of purposes. As a result, it is vital to efficiently utilize the reservoir's water in order to meet competing objectives. To optimize a large-reservoir system, thorough research and the development of system analytic methodologies, such as soft computing approaches, are required. In the current study, the Omkareshwar Sagar Project (OSP) Reservoir in India was optimized for target storage generation in order to satisfy annual demands, safeguard against flooding, and increase power generation. To ensure that the findings are as precise as feasible by Moth Flame Optimization (MFO), the OSP reservoir operations are optimized under two distinct monsoon situations. Optimized To maximize power output and satisfy the storage aim, a flood-proof system is required. Additionally, this work highlights the utility of Moth Flame Optimization in optimizing complex water resource systems.

Keywords: Flood, Meta-Heuristic, Optimization, Reservoir operation, Moth Flame optimization.

1. Introduction

Along with irrigation, electricity, navigation, and flood control, reservoirs have a significant economic impact on a country, especially India. Among the reservoir's conflicting but critical objectives are flood protection, maximization of power generation, and storage for future use. During floods, water is stored, kept, and released from reservoirs for a variety of purposes. As a result, it is necessary to efficiently utilize the reservoir's water for a number of purposes in order to accomplish the varied objectives. To optimize a large-reservoir system, extensive study and development of system analytic tools, particularly soft computing approaches, are required. As a result, reservoirs that perform many roles must be well-maintained to ensure proper operation and administration.

Optimization of the operations of a multipurpose reservoir requires methodical research. To optimize reservoir operations, both traditional and novel optimization techniques have been developed and used. The conventional reservoir operating approaches include linear programming (LP), non-linear programming (NLP), and dynamic programming (DP). Regardless of their efficiency, these strategies have a number of disadvantages. While LP requires a linear objective function and restrictions, DP is bound by its dimensionality, and NLP is unable to efficiently address the non-convex issue on its own [1]. [2] optimized hydropower generation in a multi-reservoir system using Non-Linear Programming (NLP). [3] used a combination of natural language processing and machine learning techniques to plan multifunctional reservoir operations. However, the quest for novel optimization algorithms capable of yielding globally optimal solutions is continuing. [4] addresses contemporary optimization methods in the planning, engineering, and management of water resources in depth. [5] created the Moth Flame Optimization (MFO) algorithm, which is one of various soft computing strategies. It is informed by moth behavior and a population-based approach inspired by nature. The use of the MFO algorithm for water resources is very recent, and Zhang et al. (2020) describe a few studies that use an upgraded version of the R-domination improved Moth Flame Optimization (R-IMFO) technique to cascade reservoir operation in the context of ecology and navigation.

These studies show that MFO is a robust method for finding global optimal solutions in the realm of water resources, and thus it is generally applicable. As part of this research, the Indian Omkareshwar Sagar Project Reservoir (OSP) was designed to meet annual demands, protect against flooding, and increase power generation. The Moth Flame Optimization (MFO) technique is used to optimize OSP reservoir operations for two separate monsoon flood wave scenarios and is also compared with the results of NLP (a conventional method) in order to test the accuracy of the results.

2. Moth Flame Optimization

Seyedali Mirjalili developed the Moth Flame Optimization (MFO) approach in 2015. Moth behaviour and a population-based approach are the foundations of this method. As a butterfly family member, the moth is drawn to light (light bulbs and the moon as they activate at night). Moths always migrate in the direction of the light source, despite the fact that they fly in a straight line and maintain an angle with the light source. There's a lot to be said for the moth-based algorithm's capacity to traverse all four dimensions of space. The best outcome of the algorithm can be determined by using only two parameters. How many moths are in a population, and how much iteration is there?

To find the best optimal solution from MFO:

$$\mathrm{MO_i} = \mathrm{S}[\mathrm{MO_i}, \mathrm{F_j}] \qquad (1)$$

Where, MO_i = i^{th} moth, F_j = j^{th} flame and S= Spiral function

It is crucial to note that in this circumstance, both the moth and the flame are valid options. Moths act as search agents (for population), and flames supply the moths with the ideal place.

The logarithmic spiral is utilized to find spiral function:

$$\mathrm{S}\left(\mathrm{MO_i}, \mathrm{F_j}\right) = \mathrm{D_i} * e^{bt} * \cos(2\pi t) + \mathrm{F_j} \qquad (2)$$

Where D_i = Distance of i^{th} moth from the j^{th} flame can be found by:

$$D_i = lF_j - M_l l \quad (3)$$

b = The logarithmic spiral's shape defining constant, and t = A random number between [-1, 1]. For further space exploration and exploitation, t can be written as [r, 1], where r is a convergence constant that decreases linearly with iteration from -1 to -2.

To avoid local optima, each moth gets one flame. In this way, each moth has an equal chance to investigate each flame's search zone. To optimize the utilization of the ideal solution, the number of flame mechanisms is reduced with each iteration.

$$\text{Flame no.} = \text{round}\left(N - l\,\frac{N-1}{T}\right) \quad (4)$$

Where, l = Current no of iteration, N = Maximum no of flame, and T = Maximum no of iteration

3. Study Area

The Omkareshwar Sagar Project reservoir is 53 meters high and 949 meters long, with eight 65 MW units. The reservoir's 987 Mcm gross capacity irrigates over 146,800 hectares of cropland. The OSP is situated between the Indira Sagar Project in Madhya Pradesh and the Sardar Sarovar Project in Gujrat, India. ISP is a huge reservoir that already discharges water under controlled conditions. The mandatory water release for SSP has made OSP more difficult to run. To protect the downstream reservoir from flooding, increase power output, target storage for future use, and ensure that the downstream reservoir receives the necessary release, OSP must be engaged.

4. Model Formulation

The objective function is defined by the above objectives. A continuity constraint is added to the objective function. The hydroelectric release is kept constant at 6.8 per hour.

$$\text{Min}\left[\sum_{t=1}^{T} \mathbf{V_1(O_t)^2 + V_2(S_{t+1} - S_t - I_t + O_t + O_{pt})^2} + \sum_{t=2}^{T+1} \mathbf{V_3(S_t - T_s)^2}\right] \quad (5)$$

Where,

Exit via Spillway, referred to as O_t When the turbine's output is selected as "O_{pt}," S_t is the amount of storage at time t, and S_{t+1} is the amount of storage at time t+1, respectively. The reservoir's target storage capacity is referred to as "T_s." O_t max is the maximum amount of water that can exit the spillway at one time. Minimum spillway outflow (O_{tmin}) and maximum turbine outflow (O_{tmax}). The objective function is constrained by the limitations on the values of the variables that are used.

$$O_{tmin} \leq O_t \leq O_{tmax} \quad (6)$$

$$O_{ptmin} \leq O_{pt} \leq O_{ptmax} \quad (7)$$

$$S_{tmin} \leq S_t \leq S_{tmax} \quad (8)$$

V1 is the spillage weight, V2 is the continuity equation weight, and V3 is the desired storage weight at the completion of the reservoir operation. Today's task has 25 values for release and storage. Multiple objective problems can be solved as a single problem by adjusting weights.

5. Result and Discussion

The OSP is utilized in this study to optimize reservoir operation while also optimizing power output, achieving target storage for future use, protecting the downstream side from flooding, and meeting the downstream side reservoir's mandated release. The non-linear model proposed above is optimized for two distinct inflow scenarios during the monsoon season, each representing a different flow state. Hydropower release is held constant at its maximum value of 6.8 Mcm to maximize power generation. The objective function assigns the following weights: V1 = 0.1, V2 = 100, and V3 is randomly adjusted between 0.00001 and 100,000, from lower to higher value, for each inflow value of the flood wave. The heuristic method used to allocate these weights ensures that the study's several objectives are accomplished in the order in which they were prioritized at the outset. The objective function is optimized using Moth Flame Optimization with a population size of 20 and 500 iterations. Fig. 1 illustrates the convergence of two flood input scenarios for the duration of the monsoon to an ideal solution. At first glance, it appears as though all of the inflow scenarios had suboptimal results, as illustrated in the image. However, after 200 iterations, the MFO converges on the optimal fitness value for both inflow circumstances.

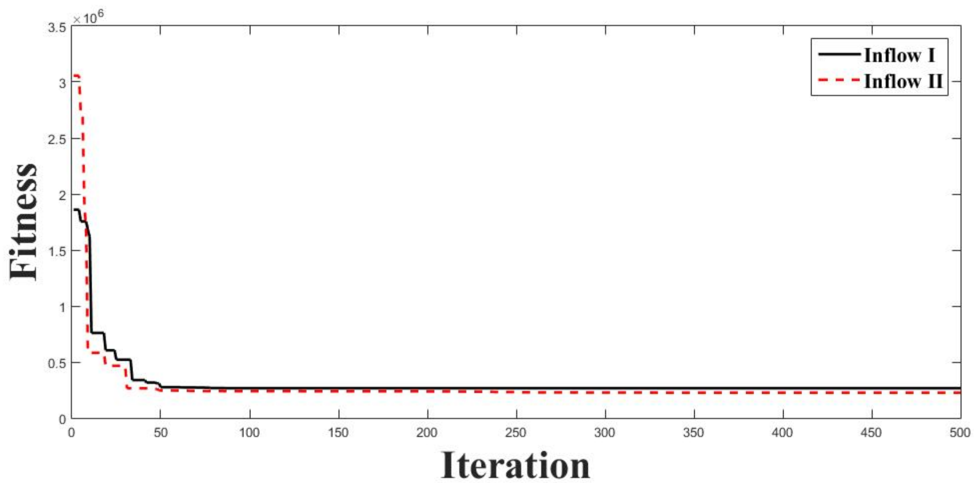
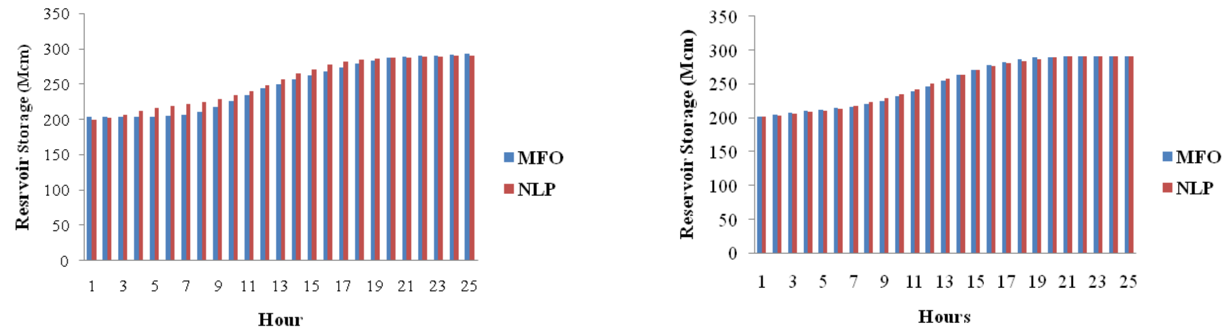


Fig. 1 Convergence of MFO to best fitness value for both flood inflow scenarios

Two distinct flood inflow scenarios are evaluated to determine the algorithm's accuracy in achieving the target storage of 299 Mcm. The MFO results were also compared to the NLP results. Fig. 2 illustrates a comparative; gradually increasing storage plot for each flood wave inflow value calculated using NLP and MFO for two distinct flood inflow scenarios. It is obvious from all of the portions of Fig. 2 that both models take a fairly similar path to reach destination storage with very slight changes. The final storage estimates derived by NLP and MFO for two distinct flood inflow scenarios are shown in Table 1. The model is compressed based on the near target storage value achieved by NLP and MFO in terms of Mcm and %. When examining Table 1, it is evident that the average percentage of target storage attained by NLP and MFO for the two separate flood inflow scenarios is 97.08 percent and 97.49 percent, respectively, indicating that MFO performs well in obtaining near-target storage.



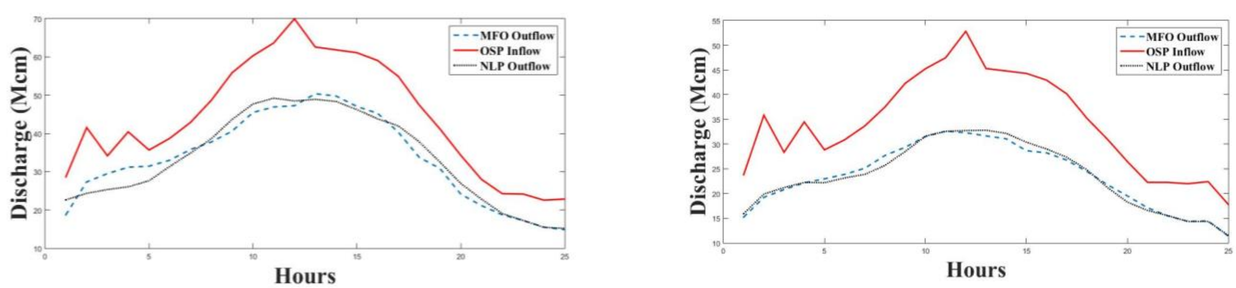
(a) (b)

Fig. 2 Comparative gradually increasing storage plot from NLP and MFO different flood inflow scenarios type (a) I, (b) II

Table 1 Target storage (299 Mcm) achievement by NLP and MFO for different flood inflow scenarios

Flood Inflow Scenario	NLP		MFO	
	Storage (Mcm)	% Achieved	Storage (Mcm)	% Achieved
I	290.221	97.0637	292.549	97.8423
II	290.335	97.1019	290.465	97.1456

The comparison inflow and outflow charts generated by NLP and MFO for two distinct flood influx scenarios are shown in Fig. 3. The discharge generated by MFO follows the form of the hydrograph and also follows the path generated by NLP with very slight deviations. The MFO generates outflow hydrographs that are smooth in shape, lower the peak of floods to safeguard the downstream reservoir, and also release the mandatory release for the downstream reservoir.



(a) (b)

Fig. 3 Comparative inflow vs. outflow plot generated from NLP and MFO in different flood inflow scenarios type (a) I, (b) II

The flood peak is shown in Table 2 for two alternative flood input scenarios using NLP and MFO. The model is compressed based on the flood peak being decreased in Mcm and percentage terms using NLP and MFO. While examining Table 2, it is clear that the average percentage of flood peak reduction achieved by NLP and MFO for the two flood inflow scenarios is 33.78 percent and 33.45 percent, respectively, indicating that MFO performs the same as NLP (the conventional method) in terms of reducing flood peak to protect the downstream side in conjunction with mandated release.

Table 2 Flood peak reduced by NLP and MFO for different flood inflow scenarios

Flood Inflow Scenario	Flood Peak (Mcm)	NLP		MFO	
		Flood peak Reduced	% Reduced	Flood peak Reduced	% Reduced
I	69.96	49.21	29.660	49.77	28.859
II	52.82	32.73	37.902	32.61	38.263

The MFO findings for both flood inflow scenarios indicate that they perform admirably in all respects, including maximizing hydropower output, achieving target storage, protecting against flooding, and meeting mandated release for the downstream side reservoir. Additionally, the MFO findings were evaluated against standard NLP results, and it was determined that MFO may be used to optimize reservoir operation difficulties during flood situations.

6. Conclusion

The OSP reservoir is optimized for hydropower generation, target storage for future use, and flood prevention on the downstream side of the reservoir, utilizing Moth Flame Optimization and Non-linear Programming to solve a non-linear model. This non-linear model is then used to satisfy the mandated release for the downstream reservoir. The MFO algorithm was used to optimize two distinct flood inflow scenarios that correspond to two distinct monsoon conditions. For a population size of 20, the best fitness outcomes are obtained by iterating the MFO algorithm for 500 iterations. The MFO method, on the other hand, obtained the global optimal solution after only 300 iterations, demonstrating the MFO's speed and robustness. Maintaining a consistent hydropower release value has resulted in the highest power generation. Both NLP and MFO obtained average near-target values of 97.08 percent and 97.49 percent, respectively, for both flood inflow scenarios, indicating that MFO performs as well as the traditional NLP method. The average flood peak is decreased by 33.78 percent and 33.45 percent, respectively, by NLP and MFO, which helps safeguard the downstream from flood conditions and also meets the downstream side reservoir's mandated release. This work also shows that Moth Flame Optimization can be used to optimize very large and complex water resources.

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