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REVIEW OF RESERVOIR OPERATION

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ABSTRACT

Reservoir operation occupies an important place in the utilization of water resources. Large-scale reservoirs play an essential role in water resource management for agricultural irrigation, water supply, and flood control. However, we need robust reservoir operation systems under both normal flow and extreme flow conditions. The use of models and decision tools for real-world reservoir operations is limited due to the gap between the models/tools and real-world practices, the tedious amount of work in case-by-case developments, and the computational difficulty of running complex numerical models. In reservoir operation, an appropriate methodology for deriving reservoir operating rules should be selected, and operating rules should then be formulated. Various algorithms and techniques are used to optimize the operation of existing multipurpose reservoirs and to derive reservoir operating rules for optimal reservoir operations. Parameter uncertainty inherent in reservoir operation affects operation model robustness and has been considered in conventional operations focusing on improving hydropower generation. With more attention being paid to ecological environmental protection recently, reversible ecosystem protection requires environmental flow (e-flow) management to sustain a near-natural flow regime. Whether there is e-flow management in reservoir operation has an impact on the uncertainty of reservoir operation. Optimizing storage reservoir operations aims to ensure that all planned reservoir objectives are met without compromising those ecological water requirements. It takes into account a variety of objectives and variables, including cost and revenue considerations of water allocation for various socioeconomic uses. Various computer simulation models can be used for optimization. The models use algorithms to calculate the optimal balance between water release and reservoir storage volumes. This era is the era ofscience and technology. There are many algorithms for the optimal reservoir, including the genetic algorithm (GA), the honey-bee mating optimization (HBMO) algorithm, the artificial fish swarm algorithm (AFSA), the particle swarm optimization algorithm (PSOA) (hybrid approach), the Jaya algorithm, and a multiobjective evolutionary algorithm (MOEA). The results obtained using the proposed evolutionary algorithm are able to offer many alternative policies for the reservoir operator, giving flexibility to choose the best out of them.

Keywords: Multiobjective optimization, Different algorithms, Reservoir operation, Hydropower

INTRODUCTION

In real life, most water resource optimization problems involve conflicting objectives, for which there is no efficient method for finding multiple trade-off optimal solutions (Aroua, 2018; Aroua, 2022). Most reservoir systems serve multiple purposes, and they are multiobjective in nature. To optimize such complex reservoir systems, dynamic programming (DP), linear programming (LP), and nonlinear programming (NLP) have been widely applied in the past (Yeh, 1985). However, when DP is applied to a multireservoir system, it involves a major problem of the curse of dimensionality, with an increase in the number of state variables. Techniques such as LP and NLP have essential approximation problems in dealing with discontinuous, nondifferentiable, nonconvex multiobjective functions (Kumar et al., 2018). Recently, there has been increasing interest in biologically motivated adaptive systems for solving optimization problems. Genetic algorithms (GAs) are one of the most promising techniques in the natural adaptive system field of the evolutionary algorithm (EA) paradigm and are receiving wide attention because of their flexibility and effectiveness in optimizing complex systems (Mezenner et al., 2022). Genetic algorithms use a population of solutions in each iteration instead of a single solution, so they are called population-based approaches (Goldberg, 1989). This is one of the most striking differences between classical optimization methods and GAs. GAs use objective function information directly and do not require its derivatives or any other auxiliary information. Sometimes this may lead to slower convergence, as it does not explicitly use derivative information (Kumar et al., 2022). GAs use randomized initialization and stochastic algorithms in their operation, so they can locate the search at any place in the search space and can overcome the problems of local optima. GAs are suitable for solving reservoir operation problems (Kumar et al., 2020).

GAs are not restricted by the number of dimensions, as computer memory requirements increase only linearly but not exponentially with an increase in dimensions (Roushangar et al., 2021). Classical optimization methods such as DP, LP, and NLP are not appropriate for multiobjective optimization because these methods use a point-by-point search approach, and the outcome is a single optimal solution (Sharma et al., 2023). Most of the classical optimization methods consider multiple objective functions using a weighted approach or constrained approach without considering all the objectives simultaneously (Azamathulla et al., 2007).

The optimization of any multipurpose reservoir system involves solving multidimensional multiobjective problems. The multimember approach, followed in evolutionary algorithms (EAs), makes them an ideal processor that can be used for solving multiobjective optimization problems (Deb, 2001). Most water resources and hydrology problems are characterized by multiple objectives and/or goals, which often conflict and compete with one another. The optimization of multipurpose reservoir systems involves solving multiobjective problems. For example, for a reservoir system with hydropower and flood control as key purposes, the two major objectives can be the maximization of hydropower generation from the reservoir and the minimization of flood risk or flood damage. These two objectives are in conflict and compete with each other. The higher the level of the reservoir is, the more hydropower generation is possible because of the high water head, yet less water storage will be available for flood control purposes and vice versa. One can identify, within the active storage capacity of that reservoir, a Pareto optimum region where the enhancement of the first objective can be achieved only at the expense or degradation of the second, namely, flood control. Additionally, the units of these two objectives are incommensurable.

The first objective, which maximizes hydroelectric power, is generally measured in units of energy and not necessarily in monetary units, whereas the second objective can be measured in terms of acres of land, livestock, or human lives saved. If the objectives are noncommensurate, the classic methods of optimization cannot be applied easily. Of the several approaches developed to deal with multiple objectives, tradeoff methodologies have shown promise as an effective means for considering noncommensurate objectives that are to be subjectively compared in operation determination (Cohon and Marks, 1975). Therefore, the efficient generation of a set of alternatives for multiple objectives is very important with minimum computational requirements. The operation of dams by considering the quantitative–qualitative characteristics of reservoir inflow and demand is a complicated process that should take into account a variety of issues. The simultaneous effects of climate change on inflow reduction and the consequent increase in demand and other changes in water quality should be considered in reservoir operation modeling.

The operation model is an important tool to study reservoir operation, but it adopts relatively simple mathematical formulas or physical equations to conceptually and abstractly describe reservoir operation, which often causes distortion phenomena (the alteration from reality to estimated decision). Because of the mutual influence of different external factors in the simulation process, a reservoir operation simulation model always has errors between the true optimal and simulation values. The resulting uncertainty from inevitable distortion phenomena and errors needs to be analyzed and evaluated to develop a robust reservoir operation model. Uncertainty always exists in the physical parameters of a reservoir operation model, such as reservoir characteristics (e.g., stage-storage curve, hydropower generation process, and parameters representing operation performance). Therefore, uncertainty in reservoir operation is a problem that cannot be ignored in modeling research.

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The world is trying to supply water in different sectors, such as drinking water, agriculture, industry, and the environment. Throughout the world, there are water reservoirs whose function is the provision of drinking water, meeting irrigation needs, flood control, and supplying water for environmental purposes. Additionally, the outflow of some dam reservoirs is used to generate electricity in downstream power plants. Even if there is great demand for the construction of dams in many countries, it is very expensive to build them. Furthermore, there are several environmental restrictions on building dams. Hence, optimizing the operation of dam reservoirs to supply maximum water is required so that in every operation cycle, water shortages for downstream consumers are minimized. In its recent report, the World Commission on Dams has placed intense emphasis on the issue that utilization optimization techniques and using dams with greater output can be a good substitute for dam construction and their ensuing expenses. The main issue in the optimization of reservoir operation is expressed as the amount of water released for downstream consumers, provided that reservoir reserves are not reduced to less than some specified levels. Another problem is the timing of the water release. Therefore, optimization of reservoir operation helps to satisfy the consumers' water needs such that the efficiency and reliability coefficient are high enough in this regard and the reservoir's supply does not diminish below the allowable limits.

Reservoir operation is complex in nature, as it has to incorporate all the input imprecision and uncertainties (Verma et al., 2023a). The output should fulfill all the system requirements, such as meeting various demands, without violating the physical constraints of the system (Verma et al., 2023b). For complex systems, no single technology can easily satisfy all the requirements of the problem. In the quest for a solution to the problem at hand, it is natural to combine more than one technology to create hybrid systems. Hybrid systems are designed to take advantage of the strengths and avoid the limitations of each system. Many successful applications of fuzzy systems have been reported in the literature, especially in control and modeling (Fontane et al. 1997; Dubrovin et al. 2002).

They are suitable for situations where an exact model of a process is either impractical or very costly to build, but an imprecise model based on existing human expertise can do the job (Waikhom et al., 2015; Zeinalie et al., 2021). In such situations, fuzzy systems are considered the best alternative, although they do not perform optimally. Fuzzy sets are an aid in providing information in a more human-comprehensible or natural form and can handle uncertainties at various levels. The knowledge contained in fuzzy systems is transparent to the user. On the other hand, ANNs are also used successfully for single-reservoir and multireservoir operations (Raman and Chandramouli 1996; Jain et al. 1999; Chandramouli and Raman 2001). While neural networks are ideal for modeling known or unknown associations that exist between the input and output data, significant data cleaning and preprocessing are usually needed. In other words, input data must be carefully prepared for the network to process. The more input data there are, the better the training results. The richer the input data are, the more accurate the model. However, training requires substantial time and resources (Yadav et al., 2015).

These difficulties restrict the widespread use of neural networks in many applications (Badiru and Cheung, 2002). In many decision-making systems, it is important to be able to explain the process by which the decision is made. The concepts of fuzzy logic complement those of neural networks. While fuzzy logic provides simple data representation, neural networks provide none. Where fuzzy logic can be used to model a system, neural networks are well suited to provide sophisticated models of diverse types of systems. However, if there is prior knowledge about the underlying system, fuzzy logic can readily encapsulate the knowledge in terms of rules and relations, while it is not particularly easy to preprogram a neural network with prior knowledge. Given a set of training samples, it is not simple to train a fuzzy model, but many algorithms have been developed in the past for training neural networks.

The concept of neuro-fuzzy hybrid systems has emerged as researchers have tried to combine the transparent, linguistic representation of a fuzzy system with the learning ability of an ANN (Brown and Harris 1994). A neuro-fuzzy system uses an ANN learning algorithm to determine its parameters, i.e., fuzzy sets and fuzzy rules, by processing data samples. Therefore, it can be trained to perform an input–output mapping, just as with an ANN, but with the additional benefit of being able to provide the set of rules on which the model is based. Deka and Chandramouli (2003) developed a fuzzy neural network model for deriving the river stage-discharge relationship at selected gauging stations of the Brahmaputra River in India and found it to be better than the other models considered. Deka and Chandramouli (2005) also found that fuzzy neural network modeling used in routing river flow was better than other models considered. Chaves and Kojiri 2007 developed a conceptual fuzzy neural network CFNN for water quality simulation in the Barra Bonita reservoir system in Brazil using a genetic algorithm as the training method for finding fuzzy inference and connection weights.

They found that the CFNN model showed greater robustness and reliability when dealing with systems for which data are considered vague, uncertain, or incomplete. In the past 30 years, the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) has become one of the most extensively used watershed-scale models across the world. It is a semidistributed, continuous-time hydrologic model with the following components: weather, surface/subsurface flows, return flow, percolation, evapotranspiration, transmission losses, pond and reservoir storage, crop growth and irrigation, reach routing, nutrient and pesticide loading, and water diversion. SWAT has been applied to perform simulations of streamflow, sediment, and water quality processes at watershed scales with over 3,800 peer-reviewed publications. It has proven to be an effective tool to quantify the impacts of anthropogenic activities such as management practices and land use changes under various climate scenarios in large watersheds (Xia et al., 2014; Abbaspour et al., 2015; Wang et al., 2016). In addition, the SWAT model has also been adopted by government agencies and policymakers, such as the Conservation Effects Assessment Project (CEAP) conducted by the Department of Agriculture, United States, and environmental assessments by the US EPA (Yen et al., 2016a). While many previous research studies and scientific projects across the globe have demonstrated the flexibility and effectiveness of SWAT in evaluating water quantity and quality subjects, several weaknesses and limitations of the model are shown to have a negative impact on future model development. By the SWAT developer group and scientists in the SWAT community worldwide, several issues have been addressed that could lead to less accurate simulation of individual processes, regional adaptations to specific environmental conditions, or linkages of SWAT with other models (Gassman, 2017). Numerous modifications have been added or revised in SWAT, which results in source code that is increasingly difficult to manage and maintain.

The flexibility for potential model improvements is limited, and the computational speed in simulations is reduced in the current structure. Therefore, a completely reconstructed version of SWAT, dubbed SWAT+ (Bieger et al., 2017; Arnold et al., 2018), has been released recently with entirely new coding features. SWAT+ is more flexible than SWAT in terms of spatial representation, and the associated modular codes are designed to facilitate future applications and development for general users. The advancement of the SWAT+ model is expected to continue in the worldwide SWAT community, and the number of innovative applications continues to grow. Water is a vital resource that supports all forms of life (Pimentel et al., 2004). Unfortunately, water is not evenly distributed by location or by season across the globe. Some areas are arid, and water is a scarce and precious commodity, whereas some receive excess rain, causing flooding with loss of lives and property (Schultz et al., 2017). Throughout history, reservoirs and dams have been constructed to collect, store and manage the supply of water, which can provide benefits such as flood and drought control, recreation, fishery, wildlife habitats, and hydroelectric power generation. The impacts of reservoirs on water are substantial to the hydrologic cycle, causing significant effects, as reservoirs are interconnected throughout most river networks (Kim, 2013). Reservoir operation may vary substantially by the initiated purposes and goals. Research work can be found when different scientific targets are selected. For instance, hedging rule policies were investigated by analyzing the corresponding water availability demands and inflow uncertainty (You and Cai, 2008).

Flushing strategies were developed by using network flow programming to better represent and compromise the potential conflicts between sediment load releases versus the goal of maximizing water supply (Chou and Wu, 2016). However, it is difficult to develop universal reservoir operation routines or models for all possible cases. The development of realistic reservoir models can be tedious, whereas sophisticated algorithms such as data mining or linear/dynamic programming may be required (Hejazi and Cai, 2011). Therefore, most reservoir operation functions are embedded in programs with multiple tasks. For example, reservoir operation was incorporated with fish ecosystem restoration in east-central Illinois, United States (Yang and Cai, 2011). In this case, the fish community is the primary research subject, and reservoir operation is only the associated technical section. However, within the SWAT model, the reservoir module was simplistic and did not always provide an accurate estimation of reservoir releases and ultimately stream flow, sediment, and load nutrients.

It is complicated to build a better reservoir module in the current SWAT framework because of the limitations in the model structure. For instance, in the SWAT application in the Mekong River Basin, Vietnam (water release and the consequence of hydropower generation), it was found that the default SWAT framework cannot properly simulate complex hydrologic processes with a large number of reservoirs in the system (Khan et al., 2017). One has to manually revise the source code in each case study to provide scientifically reliable results. In addition, for national-scale environmental assessment (e.g., CEAP), even a simple, robust reservoir operation module that can be easily parameterized for all reservoirs in the U.S. is still needed. Thus, it is timely important to add a new reservoir release module into SWAT+, taking advantage of its modular structure (additional functions can be incorporated flexibly into the SWAT+ framework). The new functions of reservoir operation require additional parameters (a total of 15).

Users may be confused about the associated functionalities, and the recommended ranges of parameters are not yet defined. In this study, the automatic calibration program Integrated Parameter Estimation and Uncertainty Analysis Tool (IPEAT, Yen et al., 2014; Yen et al., 2019) was coupled with SWAT+ to conduct reservoir operations. IPEAT has been shown to have pronounced flexibility in integrating with watershed models such as SWAT and Agricultural Policy/Environmental eXtender (APEX) (Wang et al., 2014). Users can take advantage of the IPEAT platform to perform calibration work efficiently. The primary goal of this study is to develop a more realistic reservoir module for SWAT+ with recommended parameter ranges for national environmental assessments and the user community. Specifically, three objectives are defined: (i) develop a reservoir release model based on outflow-storage relationships; (ii) incorporate the release model into SWAT+ and optimize parameters by using IPEAT; and (iii) provide recommended parameter ranges for reservoirs in the CONUS. More than 120 reservoirs across the CONUS were simulated.

Efficient planning and management strategies are essential for the optimum utilization of resources and are considered a process for continuous improvement and sustainable development. Additionally, it is necessary to formulate mathematical models and introduce new techniques to solve them for planning efficient strategies. In the present study, three nontraditional optimization techniques, namely, simulated annealing (SA), simulated quenching (SQ), and real-coded genetic algorithms (RGAs), are employed in a case study of the Mahi Bajaj Sagar Project, India, with the objective of maximizing the annual net benefits that provide the optimum cropping pattern, storage and release policy with consideration of the conjunctive use of surface and groundwater. The study is divided into a literature review, a description of various techniques employed in the study, a case study, mathematical modeling, and results and discussion, followed by conclusions.

RESULTS AND DISCUSSION

To apply GA to the above-formulated model, average annual inflows into the reservoir have been used. The inflow scenarios represent normal seasons in the region. The parameters used in applying the GA to the reservoir operation model were studied through sensitivity analysis by varying each of the above-formulated parameters. The important input variables in the present GA model study are the monthly inflow into the reservoir system, the monthly irrigation demand, water supply, and industrial demands. The main objective of the study is to compute the quantity of water that should be released to meet the monthly irrigation demand. Since the fitness function is based on the monthly irrigation demands (Dt), monthly inflow in the reservoir (It), and other monthly demands, reservoir releases for irrigation (Rt) and initial storage (St) in the reservoir in the monthly time step are chosen as decision variables. Thus, twenty-four decision variables are considered. The fitness function evaluation gives the measure of the goodness of fit of the string. After fitness, the population size is increased up to a certain population size. With a further increase in population, the system still performs better, but no significant improvement occurs. In the present study, the significant point occurs at 250, and after that, the performance has not improved significantly. The genetic algorithm (GA) has been used to optimize the operation of existing multipurpose reservoirs in India and to derive reservoir operating rules for optimal reservoir operations. A comparative plot of actual demand and GA model release for an average inflow is shown in Fig. 1. Fig. 1 shows that the demand is almost satisfied with the releases obtained through the GA model. To derive the rule curve, the results obtained are plotted in Fig. 2 (Shiyekar et al., 2016).

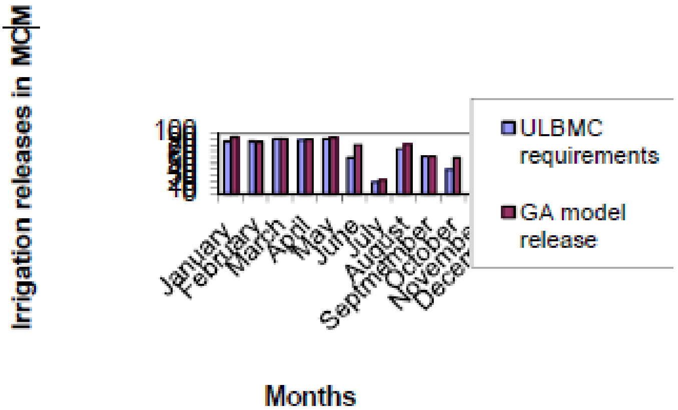

Figure 1: Monthly irrigation demand and releases as per the GA model for ULBMC (Shiyekar et al., 2016)

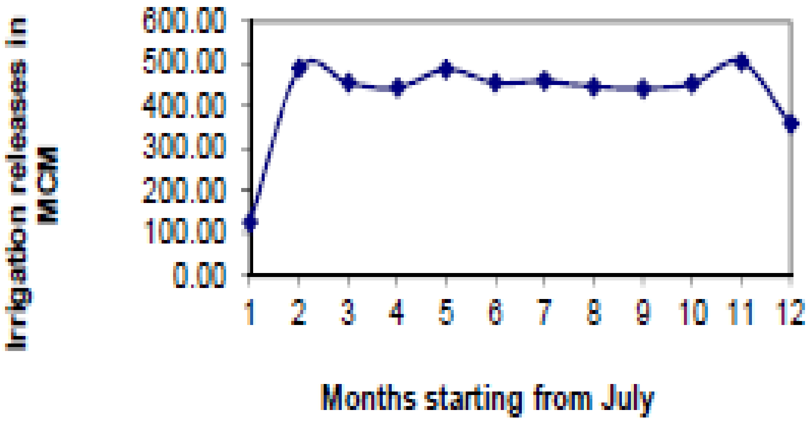

Figure 2: Monthly irrigation releases at different inflows (Shiyekar et al., 2016)

The parameters used in applying the GA to the reservoir operation model were those selected after a thorough sensitivity analysis by varying each of the parameters. A population size of 250 and a crossover probability of 0.75 are chosen to run the model. The amount of water released for irrigation for each month. These rule curves show the final storage to be maintained in the reservoir in each month starting from June under inflows. Storage is maximum at the start of October, i.e., when the monsoon reaches its peak and consequently decreases to a minimum in July to receive the next monsoon inflow, reduce flood damage and reduce water losses from the system. This region falls under the assured rainfall zone, so the minimum target level to be achieved is kept as dead storage and is achieved at the start of the monsoon season.

The four-reservoir systems are a benchmark problem of reservoir operation optimization that has been used to compare the performance of various strategies proposed in the domain. JA was first applied to the Four-Reservoir system (benchmark) to test its applicability to reservoir operation studies. With its success in this benchmark study, it has been further applied to optimize the operation of the Mula reservoir, Upper Godavari Basin, India. The results of the two case studies are explained in the next sections.

Results of various algorithms for the Rastrigen and Bulkin-6 functions

The parameters of the algorithms are obtained from 30 runs based on sensitivity analysis. Because of the necessity for examining the stability of the algorithm and assuring high confidence, 30 runs are applied to investigate the proposed algorithms. Benchmark functions are necessary to evaluate the new proposed algorithm. In this research, the proposed AFSA was developed based on MATLAB interface coding, while the other methods have been recalled from the literature for comparative analysis purposes. The results achieved benchmark functions based on the results achieved in previous studies and reported in associated references and in addition to the one achieved based on the newly proposed method.

Fig. 3 shows the performance of daily reservoir outflow simulations for 123 reservoirs across the whole CONUS. The NS values in most reservoirs ranged from 0.1 to 0.7, while several were larger than 0.5 (Wu et al., 2020). For PBIAS, values in most reservoirs ranged from −10 to 10. In addition, almost all reservoirs with low NS had satisfactory PBIAS values. Therefore, the performance of the daily reservoir outflow simulation was overall satisfactory based on both PBIAS and NS (Moriasi et al., 2007). Histograms of probability for 15 parameters based on reservoir release classification R2 in the reservoir model in SWAT+, given by Wu et al. (2020), are easy to attain with general release rules. However, it is difficult to obtain highly accurate daily release rates (NS) due to specific local conditions, such as irrigation demand and downstream flooding concerns. The observed mean outflow and highest outflow were further compared in the 123 selected reservoirs, as shown in Fig. 3.

The simulated daily mean outflow was highly consistent with the observed mean outflow, with a correlation coefficient R almost equal to 1. For high outflow, the simulation performance in most reservoirs was satisfactory (R = 0.69), while overestimation for high flow was found in a few reservoirs (e.g., Number 5, 33, 91, and 120). In brief, from the perspective of the mean and high outflow, the simulation performance in most reservoirs was relatively satisfactory. Furthermore, the two best daily simulated and observed outflows were displayed from 1994 to 2015. The simulations underestimated the high outflow in the Great Salt Plains Reservoir, while in the Caddo Reservoir, the simulations overestimated the high outflow. In general, daily outflow simulations in both reservoirs were mostly under the statistical category of satisfactory.

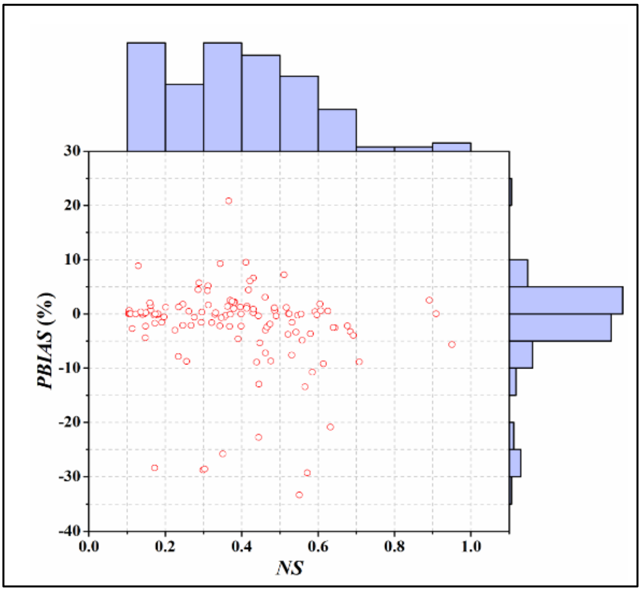

Figure 3: Model performance of daily reservoir outflow simulations in 123 selected reservoirs (Wu et al., 2020)

The MOGA approach is applied to the Bhadra reservoir system to derive operating policies for the multipurpose reservoir system under multiple objectives. In general, for any multiobjective optimization problem, no single solution is said to be optimal, and fortunately, with the MOGA approach, it is possible to generate different alternatives in a single run, which helps in plotting the transformation curve between the objectives, which consequently helps the decision maker to make a suitable decision. Figure 3 shows a set of well-distributed solutions along the Pareto optimal front for the three different inflow scenarios, viz., dry, normal, and wet seasons. In multiobjective optimization, after arriving at the Pareto front, the remaining task is decision-making, which requires a subjective judgment by the decision-maker based on his preferences. The MOGA model generates a large number of alternatives. To choose the best solution among the many alternatives, preliminary treatment of the solution is thus generally needed, which in some cases may be computationally cumbersome. To facilitate ease of decision-making, filtering is performed using a simple clustering technique to obtain a representative subset of the nondominated points. In Figures 4a, b, and c, the points of shaded dots represent a total of 200 nondominated points that were generated, while the points of dark diamonds represent the 20 filtered nondominated solutions (Reddy et al., 2006).

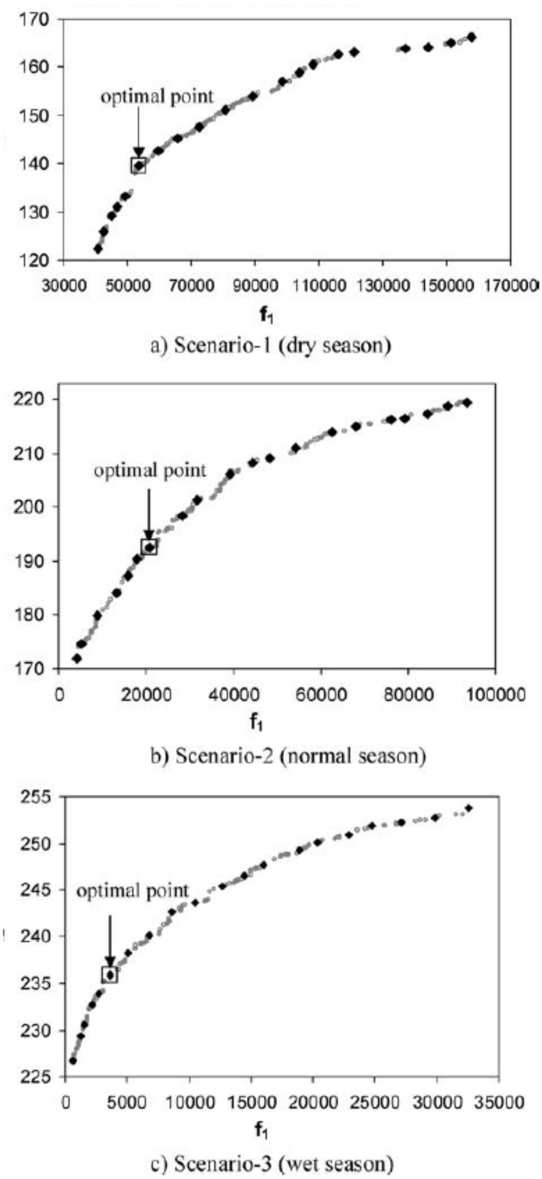

Figure 4: Pareto optimal front, showing the trade-off between irrigation (f1) and hydropower (f2) for different inflow scenarios. (f1 = sum of squared irrigation deficits, (Mm3)2; f2 =hydropower generated, MkWh) (Reddy et al., 2006)

When there is equal priority for irrigation and hydropower, it aims at concurrently maximizing benefits from both objectives. The points shown in square boxes represent the compromise solutions. For the selection of these optimal points, the marginal rate of substitution approach (Deb, 2001) is used. The marginal rate of substitution is the amount of improvement in one objective function, which is obtained by sacrificing a unit decrement in any other objective function. The solution having the maximum marginal rate of substitution is the one chosen by this method. Thus, the optimal point is the solution that corresponds to the maximum slope for the two-objective Pareto front. Therefore, the optimal points are chosen in such a way that the compromised highest net benefits can be achieved with respect to both objectives. Alternative storage and release policies can help the reservoir operator make a suitable decision for different inflow scenarios and priorities. The multiobjective GA approach is thus very useful in producing a well-defined solution set for conflicting objectives and eventually helps for better operation requiring a short computational time.

CONCLUSION

In this review, we have reviewed and analyzed various concepts and algorithms related to reservoir operation. We will give an overview of recent literature related to reservoir operation studies. The GA approach is applied to the Upper Wardha Reservoir system to derive operating policies for multipurpose reservoir systems with a single objective. The sensitivity analysis of the GA model applied to this particular reservoir suggests an optimal population size of 250 and a probability of crossover of 0.75 to find optimal releases for the Upper Wardha reservoir. The model resulted in irrigation releases equal to irrigation demand. Minimum storage is observed at the start of the monsoon, i.e., at the end of the water year, and maximum storage is observed when the monsoon reaches its peak. These types of rule curves are expected to be useful in the real-life implementation of reservoir operation. JA has been implemented and applied to two case studies, with the aim of contributing to the optimal use and sustenance of reservoir systems. When the JA was applied to a hypothetical four-reservoir system, it provided the optimal resource allocation results for the lowest FE values. The JA has been successfully applied to the mentioned four-reservoir system problem with faster convergence than other algorithms. With the increasing need for water resources and the associated requirements, reservoir operation optimization is of great importance. In this study, an attempt has been made to have better releases in comparison to the existing policy releases; therefore, JA has been applied to the reservoir operation optimization of Mula Reservoir, an existing installation in the Upper Godavari Basin, India. It was optimized for different probable inflows and was simulated for a scarce to wet period. The releases thus obtained from the simulation corresponding to an average inflow have been compared to those from existing ones. As a result, better releases were obtained with the help of the JA model in terms of maximum utilization of resources and better allocation of resources in terms of their need during the lean period. Hence, from this study, it can be concluded that JA was successful in achieving better operational releases for the Mula Reservoir. Therefore, it can be summarized that JA can be further explored for other case studies and for the more complex problem of multireservoir systems. A hybrid method of AFSA and PSOA is introduced in which it increases the variety of results in PSOA and adds group movement and follow-up operators. To verify the hybrid method, it is first implemented on a few mathematical functions, and by using the Wilcoxon statistical test, 28 mathematical functions of the Central Europe Conference 2013 are optimized or minimized. The results are compared with some other evolutionary algorithms to confirm the superiority of this new method. Additionally, to minimize power shortages in the Karun-4 power plant, this method is used and tested with various indices and a multicriteria decision-making method, which indicates that the hybrid method ranked first and is superior to other methods. In future studies, this method can be implemented on multireservoir systems, including multiple power plants, or combined with fuzzy methods. The main novelty of the present study is its introduction of a new hybrid method for the optimization of water resource management. This method increases the convergence speed of the artificial fish swarm algorithm (AFSA). Additionally, due to the potential of the absolute optimum search tool in the particle swarm optimization algorithm (PSOA), it is expected that the AFSA will not be trapped in local optima. In addition, by adding follow-up and group movement operators to the PSOA, this hybrid approach strengthens the particle group based on the diversity of the particles and augments the solution candidates by adding new groups. Moreover, it solves the premature convergence problem of the PSOA. This hybrid algorithm resolves the problem of imbalance between scanning and exploitation in AFSA. Scanning capacity is the algorithm's capability to search the search space freely, regardless of its achievements during the search process. Obviously, the higher this capacity is, the more random and unpredictable the behavior of the algorithm will be. For the sake of reinforcement, the property to profit causes the algorithm to be more cautious; therefore, it is very important to reach a balance between these two capabilities. The resultant hybrid algorithm in this study enhances this equilibrium. We focused on applying stochastic programming to water resource management. We built one operation model for reservoir operation for operating rule derivation. With a case study of China's Three Gorges Reservoir, long-term operating rules are obtained. Based on the derived operating rules, the reservoir is simulated with the inflow from 1882 to 2005, in which the mean hydropower generation is 85.71 billion kWh. The SDP works well in reservoir operation. In this study, a multiobjective genetic algorithm (MOGA) approach was applied for the optimization of a multiobjective reservoir operation problem. In the MOGA method, a nondominated sorting approach is used, which has a selection operator, elitism mechanism and crowded distance operator to obtain efficient solutions. A multiobjective model is formulated with irrigation and hydropower as two competing objectives, and the MOGA is applied to derive reservoir operation policies for the Bhadra reservoir system in India. The model is applied for three different inflow scenarios, and the corresponding Pareto optimal fronts are obtained for the three scenarios. Additionally, in this study, three kinds of priorities of the two objectives are analyzed, and the respective operating policies are presented. The main advantage of the MOGA approach is finding many Pareto optimal solutions in a single run, which is attractive and efficient and helps the decision maker make suitable decisions at different levels. Thus, this study has successfully demonstrated the efficacy and usefulness of different algorithms for evolving multiobjective reservoir operation policies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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