Modeling Multi-Objective Pareto-Optimal Reservoir Operation Policies using State-of-the-art Modeling Techniques

Aadhityaa Mohanavelu[1], Soundharajan Bankaru-Swamy[1], and Ozgur Kisi[2]

[1]Department of Civil Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore 641112, India
[2]Civil Engineering Department, Ilia State University, 0162 Tbilisi, Georgia

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Abstract

A novel challenge faced by the water scientists and water managers today is the efficient management of the available water resources for meeting crucial demands such as drinking water supply and irrigation at the same time ensuring sufficient water is available for other critical activities such as hydro-power generation. Modeling of optimal operation polices is imminent for better management of reservoir systems especially under competing multiple objectives such as irrigation, flood control, water supply etc., with decreasing reliability of these systems under climate change. This study compares six different state-of-the-art modeling techniques namely; Deterministic Dynamic Programming (DDP), Stochastic Dynamic Programming (SDP), Implicit Stochastic Optimization (ISO), Fitted Q-Iteration (FQI), Sampling Stochastic Dynamic Programming (SSDP), and Model Predictive Control (MPC), in modeling pareto-optimal operational policies considering two competing reservoir operational objectives of irrigation and flood control for the Pong reservoir system in Beas River, India. Pareto-optimal (approximate) set of operation policies were derived using the six methods mentioned above based on different convex combinations of the two objectives and finally the performances of the resulting sets of pareto-optimal operational solutions were compared with respect to resilience, reliability , vulnerability and sustainability indices. Modeling results suggests that the optimal-operational solution designed via DDP attains the best performance followed by the MPC and FQI. The performance of Pong reservoir operation assessed by comparing different performance indices suggest that there is high vulnerability (˜0.65) and low resilience (˜0.10) in current operations and the development of pareto-optimal operation solutions using multiple state-of-the-art modeling techniques might be crucial for making better reservoir operation decisions.

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[2] Civil Engineering Department, Ilia State University, 0162 Tbilisi, Georgia

*Correspondence: E-mail: aadhityaa65@gmail.com

Abstract

A novel challenge faced by the water scientists and water managers today is the efficient management of the available water resources for meeting crucial demands such as drinking water supply and irrigation at the same time ensuring sufficient water is available for other critical activities such as hydro-power generation. Modeling of optimal operation polices is imminent for better management of reservoir systems especially under competing multiple objectives such as irrigation, flood control, water supply etc., with decreasing reliability of these systems under climate change. This study compares six different state-of-the-art modeling techniques namely; Deterministic Dynamic Programming (DDP), Stochastic Dynamic Programming (SDP), Implicit Stochastic Optimization (ISO), Fitted Q-Iteration (FQI), Sampling Stochastic Dynamic Programming (SSDP), and Model Predictive Control (MPC), in modeling pareto-optimal operational policies considering two competing reservoir operational objectives of irrigation and flood control for the Pong reservoir system in Beas River, India. Pareto-optimal (approximate) set of operation policies were derived using the six methods mentioned above based on different convex combinations of the two objectives and finally the performances of the resulting sets of pareto-optimal operational solutions were compared with respect to resilience, reliability, vulnerability and sustainability indices. Modeling results suggests that the optimal-operational solution designed via DDP attains the best performance followed by the MPC and FQI. The performance of Pong reservoir operation assessed by comparing different performance indices suggest that there is high vulnerability (~0.65) and low resilience (~0.10) in current operations and the development of pareto-optimal operation solutions using multiple state-of-the-art modeling techniques might be crucial for making better reservoir operation decisions.

Keywords: Optimal reservoir operations; Multi-objective optimization; Pareto-optimal operation; State-of-the-art reservoir modeling; Reservoir management; Reservoir performance

1. Introduction

Surface water reservoirs are amongst the most important component of a water resource system and they primarily function to regulate the natural flow of stream or river by storing surplus water when there is high inflow and release the stored water during the drier months to supplement the reduction in the river discharge (Loucks and Van Beek 2017; Jain 2019). Reservoir management is a complex process since it is often quite difficult to allocate the available water for different purposes such as water supply (can be for drinking or commercial), irrigation and hydro-power generation while at the same time ensuring various demands/requirements expected from the system are satisfied within their physical constraints (Adeyemo 2011; Wurbs 1991). These requirements include maintaining sufficient storage to reduce the risk of water shortages for crucial actives during dry periods (e.g. domestic water supply), flood control/regulation and maintaining adequate environmental flow to support dependent ecosystems along the stream, river, etc. (Votruba and Broža 1989). Reservoir operational polices are developed using different techniques to help the reservoir operator to make the release decisions (Hakimi-Asiabar et al. 2010; Reddy and Kumar 2006; Tayebiyan 2016). These policies are developed based on the inflow characteristics, antecedent conditions, demand, weightage for competing objectives (e.g. hydro-power generation and flood control) under multi-objective operational conditions, historic knowledge of inflows and discharge decisions and discretion of the operator who make the release decisions (Dobson et al. 2019). Developing pareto-optimal operational solutions (pareto-optimality refers to a situation where it is not feasible to improve any objective without degrading at least one other objective) might be the most practical strategy to make reservoir operations under competing demands (Reddy and Kumar 2006; Castelletti et al. 2014; Yang et al. 2009).

Decision making of reservoir operation is complex, since it may involve thousands of decisions variables based on the objectives of the operation and constraints of the system (Yeh 1985). Some physics-based hydrological models such as Streamflow Synthesis and Reservoir Regulation (SSARR) model and HEC-5 model are being widely used throughout the world for multi-objective reservoir system modeling (Ozkaya and Zerberg 2021; Ahn et al. 2018). However, these hydrological models have several limitations due to uncertainty in the input data, difficulty in the interpretation of results and finally due to the intrinsic limitations of the model (McMahon 2009; Dang et al. 2020). To overcome the shortcoming of physics based models, different techniques from management sciences and operations research along with optimization algorithms have been widely used to manage water reservoir systems (Yeh 1985; Heydari et al. 2015). One advantage of using these data-based methods over physically-based methods (e.g. HEC-5 model) is their ability to model with very few input variables (mostly only inflow time series is sufficient), which also significantly reduces uncertainties and biases caused by errors or assumptions in the input data and antecedent conditions (Uysal 2016; Turner et al. 2020). Although no particular general algorithm for modeling reservoir operation exists, the choice of the method depends upon various factors including the physical characteristics of the systems, objectives of operation, data availability and the specified constraints (Pulido-Velazquezet al. 2016; Kaczmarek and Kindler 1982; Dobson et al. 2019). In general, the data-driven reservoir operation models can be classified as, simulation models, linear programming, dynamic programming and non-linear programming (Yeh, 1985). However, all these models have several limitations either due to curse of dimensionality, curse of modelling and curse of multiple objectives or due to a combination of these curses (Powell 2007; Giuliani et al. 2016a; Dobson et al. 2019). To overcome these limitations, combinations of the above mentioned methods along with other optimization techniques (e.g., particle swarm optimization, gradient evolution algorithm, genetic algorithm, etc.) are generally used for reservoir operation modeling (Samadi-koucheksaraee et al. 2019; SS et al. 2020; Ghimire and Reddy 2013). In addition to this, ensemble of several machine-learning and hybrid algorithms have recently been used to model optimal reservoir operations (Yang et al. 2019; Zang et al. 2019). Table 1 lists the recent studies undertaken using advanced techniques to model and optimize reservoir operation policies.

Although several models and algorithms are widely available to model and optimize reservoir operation policies there are several limitations in developing optimal release solutions either due to the intrinsic shortcomings of the model, lack of sufficient data, of bias or error in the input data, or inefficiency in the prediction of inflow and demand (McMahon 2009; Jain 2019). In addition to this, the complexity of the problem (getting an optimal operation solution) increases multi-fold as the objectives of the reservoir operation increases (Keckler and Larson 1968; Curry and Dagli 2014). Dynamic programming (DP) methods such as stochastic dynamic programming and deterministic dynamic programming are used for a long time to develop optimal reservoir operation policies, the advantages and disadvantages of these models are understudied especially under real-world conditions (Ilaboya et al. 2011). Several methods such as implicit stochastic optimization, sampling stochastic dynamic programming, etc. with other techniques such as concave objective optimization have been developed to improve the computational of the DP methods (Loucks 1993; Kelman et al.

1990; Zhao et al. 2012; Zeng et al. 2019). In addition to this, several novel metaheuristic methods such as model predictive control (a control approach which controls a process by satisfying a set of constraints in real-time), fixed Q-iteration (a batch-mode reinforced learning which uses reinforced learning techniques and functional approximation of value function) and evolutionary multi-objective algorithms such as MOEA/D-AWA and MOEA/D-DE are being used for developing optimal reservoir operation policies under competing operation objectives (Castelletti et al. 2010; Lin et al. 2020; Sun et al. 2018). Though these novel methods (including both machine learning and metaheuristic techniques) have several advantages over the conventional dynamic programming models say in terms of better accuracy and ease of modeling, these methods have several limitations as well and some them includes the requirement of huge volume of data, more computational time to derive and optimize the solution and higher difficulty in improving the computational efficiency of the model (Ezugwu et al. 2021; Teng and Gong 2018). However, application of these models to real-life reservoir operations are also very limited and hence more case studies are needed to check the validity and reliability of these models under real-world operations (Giuliani et al. 2016).

In this study, six proven state-of-the-art reservoir operation modeling techniques namely Deterministic Dynamic Programming (DDP), Stochastic Dynamic Programming (SDP), Implicit Stochastic Optimization (ISO), Fitted Q-Iteration (FQI), Sampling Stochastic Dynamic Programming (SSDP) and Model Predictive Control (MPC) has been applied to model optimal reservoir operation policies for a real-life water reservoir system called Pong Reservoir located in Beas River India. Pong reservoir is an important water storage structure in the region enabling water security, sustaining agriculture and in protecting the low lying regions from flooding. Though few modeling studies has been undertaken to model the operation of Pong reservoir, deriving daily optimal reservoir operation policies have not been performed yet and the six methods used in this study has not been previously applied for developing optimal reservoir operations for the Pong reservoir system. All the techniques were used to develop daily operation policies for the Pong Reservoir with two competing release objectives of irrigation and flood control. The trade-offs between the competing objectives was determined and the performance of different optimal operation solutions developed using the state-of-the-art modeling techniques were compared in the Pareto-optimal front. The application of different state-of-the-art models on a same case study would contribute in understanding the applicability of the different reservoir operation models for the optimal operation of any reservoir in question (Pong reservoir in this case) and help the reservoir operator in making better release decisions. Finally, the performance indices of the reservoir namely resilience, vulnerability, reliability and ultimately the sustainability were calculated to determine efficiency of the operation policies and the gaps for development.

2. Study Area and Data

Pong dam and reservoir (also called Maharana Pratap Sagar) is located in the Beas River, Himachal Pradesh, India, is among one of the major tributaries of the Indus River Basin located in Northern India, as shown in Figure 1. Pong is one of the largest earth fill dams in India with a catchment area of 12,561 km^2 in which also includes a permanent snow catchment of 780 Km^2 (Jain el al. 2007). The salient features of the Pong reservoir are provided in Table 2. Inflow to the Pong reservoir is contributed by both snow-melt and the Indian Monsoon rainfall (majorly during July –September) in the Beas catchment along with the discharge of the Pandoh dam in the upstream of Pong (Kumar et al. 2007). The water stored in the Pong primarily meets an irrigation demand of 7912 Mm^3 per year to sustain agriculture in 1.6 Mha of command area, in addition to its use for hydropower generation (capacity 396 kW) (Soundharajan et al. 2016). Wheat, paddy and cotton are the major crop cultivated in the pong command area. Studies related to Pong suggest that the satisfactory performance of Pong is susceptible to disturbances caused by variations or changes in the inflow resulting from climate change. Monthly average inflow and release of (Figure 2) Pong reservoir shows that both the inflow and release during the monsoon period is high which could be attributed to increased inflow from monsoon rainfall and high water requirement of water intense paddy irrigation in the rice cultivation season between June and October. Alternatively, from Figure 3. We can also infer that Pong is crucial for sustaining irrigation and other activities since the average demand for irrigation alone is much higher than the natural river discharge (except during monsoon) throughout the year. As a consequence of climate change, the increased inflow from snow melt and variation in the monsoon rainfall in the catchment has compounded the non-linearity of inflow into the Pong reservoir system thereby increasing the difficulty in planning the operation of Pong especially during the months from June to September.

Daily time series (Figure 3) of reservoir inflow, release and reservoir storage/water level time series from January 2008 to December 2010 were used for modeling. The reservoir flows and levels illustrated in Figure 3, reveals the significantly higher inflows during the Monsoon season. In addition to this, information including surface and catchment area, storage capacity and geometric information provided in Table 2 was used to define the modeling constraints.

3. Methodology

3.1 Overview

Daily reservoir operation policies were developed for two competing release objectives of irrigation and flood control for the Pong Reservoir system in Beas River India. The case study was implemented using the Multi-Objective Optimal Operations (M30) toolbox in Matlab which allows the implementation of different state-of-the-art techniques to design pareto-optimal operation policies for multi-purpose water reservoir systems. Source code of the models (provided in a modular structure) with details of libraries and functional files used for simulation are provided with clear explanations in the GitHub repository (https://github.com/mxgiuliani00/M3O-Multi-Objective-Optimal-Operations). The reservoir operation problem was formulated as a non-linear, periodic, discrete-time, Stochastic Markov Decision process with three input variable vectors namely state x_t (storage), control u_t (release decision) and stochastic disturbance ε_t (inflow). Each objective function J^m which is considered to be a cost was formulated as a function of the above-mentioned variable vectors as: $J^m = \lim_{n\to\infty} \gamma_{\varepsilon_1 \ldots \varepsilon_n}(\sum_{t=0}^{n-1} \gamma^t g_{t+1}^m(x_t, u_t, \varepsilon_{t+1})$ (equation 1), where n is the time horizon generally assumed to be infinity, g_{t+1}^m is the m h immediate cost function (with m=1….,M) with time varying between t and t+1 and γ is the discount factor.

The development of reservoir operation policies were performed under the assumption that the reservoir system is stationary (i.e., ignored the seasonality) to restrict the real operation conflict between the flood control and irrigation supply release objectives. Additional details about the modelling procedure is available at Giuliani et al. (2016).

3.2 Models Used

A brief description of the six models used in this study are provided in the following sections.

3.2.1 Dynamic programming

Dynamic programming methods are most likely the widely used methods for designing optimal reservoir operations. A singular feature for such popularity of DP models can be attributed to its ability to handle non-linearity in both constraints as well as the objective functions (Puterman 2014). DP converts the optimal reservoir operation problem into a sequential decision making process and the decisions made in at a particular time step affects immediate costs in addition to all the subsequent costs (Loucks and Van Beek 2017).

3.2.1.1 Deterministic Dynamic Programming

DDP consists of three major components: regression; deterministic dynamic program and simulation. DDP uses a deterministic inflow time series for dynamic program and a restricted set of storage values with an assumption of a hypothetical loss function which accounts for non-ideal reservoir operation (Harley and Chidley 1978). The solution of the dynamic program entails optimal storages x_{t+1*} and optimal releases u_{t*} for the whole time horizon considered ($t_{1,\,2\ldots}t_n$) (Karamouz and Houck 1987). The optimal releases are regressed against other operation constraints to define the general operation rules $\hat{u}_{t*}$=au_t+b$x_t + c$ where, $\hat{u}_{t*}$ is the optimal release decision and a, b, c are the coefficients of general operating rules (Karamouz and Houck 1987).

3.2.1.2 Stochastic Dynamic Programming

Operation of reservoirs is itself a sequential stochastic decision. SDP model uses the best inflow forecasts (probabilistic) as a state variable instead of using observed (deterministic) inflow as in DDP, thus taking into account the uncertainty associated with forecasts while an operation policy is established (Trezos and Yeh 1987; Stedinger et al. 1984). The fundamental concepts (say state, stages and principle of optimality) of SDP and DDP are same, however, the state transformation function varies (Kjetil 1994). In DDP state transformation function is given by $x_{k-1} = t_k(x_k, u_k)$, while in SDP the function relationship is defined as $x_{k-1} = t_k(x_k, u_k, \xi_k)$ where $x$is storage, u is release, t_k is the transformation function and ξ_k is a stochastic variable.

3.2.2 Sampling Stochastic Dynamic Programming

SSDP utilizes the complex spatial and temporal characteristics of the reservoir inflow by considering huge number of sample streamflow sequences with an assumption the streamflow variability is an empirical distribution (rather than probabilistic description as in

SDP) (Faber and Stedinger 2001; Kelman et al. 1990). SSDP overcomes the DP curses of modeling by allowing better characterization of streamflow which is oversimplified in DP (Côté and Arsenault 2019). The policy designs in SSDP are assessed by simulation over different inflow scenarios while simultaneously maintaining the streamflow hydrograph, hence both flow and spatial correlation are accurately maintained (Giuliani et al. 2016).

3.2.3 Implicit Stochastic Optimization

ISO builds on optimal operation policies derived with deterministic optimization and considers several different inflow scenarios under varying system functioning conditions (Celeste et al. 2009). ISO is structured in the following procedure. First, the sequence of optimal release decisions for an inflow time series sequence is determined through DDP, next, a set of variables are selected to condition the derived operation policy, and finally, a regression analysis is performed between release decisions obtained from DDP and the variables selected to define a function mapping (Giuliani et al. 2016). While different functions such as polynomial, fuzzy rules and neural networks can be used employ regression in the ISO procedure, in this case study we have used the Standard Operating Policy (derived from a piecewise linear approximation method) to map storage and reservoir release decisions.

3.2.4 Fitted Q-Iteration

Fitted Q-iteration is a value based, batch mode, offline reinforced learning method which integrates the principle of functional approximation of value function and reinforced learning algorithms (Castelletti et al. 2010; Liang et al. 2020). Since FQI considers the knowledge obtained from previously collected sample of operation decisions (either actual or simulated), the DP curses of modeling and dimensionality is outdone. Dimensionality curse of DP is mitigated in FQI by discretizing the state-control space coarsely and the modeling curse is overcome by conditioning the learning by considering exogenous variables such as rainfall, snow inflow, etc. in addition to the state variables (Giuliani et al. 2016). In this case study the approximation of value function is performed using regression tree.

3.2.5 Model Predictive Control

MPC is one of the most advanced process control techniques which is used to solve numerous open-loop control problems defined over a receding and finite time horizon (Bertsekas 2005; Agachi et al. 2016). In MPC constraints are considered explicitly and the tuning for robustness is directly performed (Garcia et al. 1989). MPC works based on an optimization-simulation approach by anticipating the future states of the system and by optimizing control objectives along the prediction time horizon which is subjected to the system constraints (Van Overloop 2006; Garcia et al. 1989). MPC overcomes the cures of dimensionality in DP since finding the optimal decision over a finite horizon does not require the estimation of the value function and it subdue the modeling curse by allowing to make updated decision at each time step with its real time control approach (Giuliani et al. 2016).

3.3 Simulation

The reservoir operation simulation was performed by considering the reservoir dynamics as a function of water stored in the reservoir using the mass balance equation $S_{t+1} = S_t + q_{t+1} - r_{t-1}$ in which S_t is the water stored at time t and q_{t+1} is the inflow that feeds the reservoir. The release r_{t-1} depends on the daily release u_t provided by the operation policy and constrained by some physical and normative constraints (Salient features presented in Table 2 were used as constraints).

Physical constraints and boundary conditions such as the maximum and minimum reservoir levels, reservoir storage capacity, dead storage, free board, etc., were used to define the zone of operation discretion (decision) space (Figure 4) for the Pong Reservoir. The determined maximum and minimum feasible release based on the assessment was used as a constraint for modeling the reservoir operation policies. Based on the operation discretion space, the modeling is performed with the assumption that the dam operator is forced to halt the dam operation completely if the reservoir level is less than 387 m and open the dam completely if the reservoir level is more than 425 m.

The general scheme of operation represented in Figure 5 was used for simulating the model. The two competing objectives of irrigation supply and flood control were defined as a two-dimensional objective function vector J =$\left| J^{Flood},\ J^{irrigation} \right|$ as in equation (1).

The immediate costs for irrigation and flooding were formulated using the expressions:

Flooding (g_t^{flood}): The daily water level excess above the flooding threshold (h^{flood}) of 425 meters, i.e., $g_t^{flood} = max\left((h_{t+1} - h^{flood}), 0\right)$

Irrigation ($g_t^{irrigation}$): The observed daily water (level) deficit compared to the demand (w) of 520 m^3/s in the downstream, i.e., $g_t^{irrigation} = max\left((w - r_{t-1}), 0\right)$

Determination of additional conditioning variables such as the maximum and minimum daily releases, calculations of step costs of flooding and irrigation objectives, level to storage (vice versa) conversions, construction of release matrices and the retrieval of optimal release decisions were also performed to run the simulation. Detailed methodology for performing the above-mentioned tasks are available in the simulation package of the M30 toolbox (https://github.com/mxgiuliani00/M3O-Multi-Objective-Optimal-Operations/tree/master/sim).

3.4 Pareto-Optimal Solution

The Pareto optimal front of the reservoir operation polices were obtained by adopting the weighting method called parametric objective function generalization (Saaty and Gass 1955). The optimization is considered as a two-parameter problem in which the solution minimizes the objective function. The mathematical expression of the two-parameter problem is to find the solution y_i (for i=1….n) that minimizes the linear form $\sum_1^n (a_i + \gamma_1 b_i + \gamma_2 c_j) y_i$ and satisfy the conditions $y_i \geq 0$ and $\sum_{i=1}^n a_{ij} y_i = a_{so}$ where, a_i, a_{ij}, a_{so}, b_i, c_i are constants and γ_1 and γ_2 are parameters.

Since all the methods used in the study are originally single-objective, the pareto-optimal front was generated by optimizing single-objective repeatedly for every single pareto-optimal point developed by performing the weighting of the objectives (The adopted weighting combinations are provided in the Table 3). Using this method we only explore the convex tradeoff curves and the corresponding gaps in concave regions.

The reservoir operation problem was solved each time for all the models using different combinations of the two objectives by using the weights mentioned in Table 3.

3.5 Reservoir performance

Key reservoir performance indices were analysed to assess the historic reservoir operation. Relevant performance measures namely- resilience (Hashimoto et al. 1982), reliability- time based and volume based (McMahon and Adeloye 2005; McMahon et al. 2006), vulnerability (Sandoval-Solis et al. 2011) and sustainability (Sandoval-Solis et al. 2011) were evaluated as follows:

(i) Time-based Reliability (R_{time}): Measure of total time period during which a reservoir is at the capacity to meet the full downstream demand without any shortages:

$$R_{time} = \frac{N_s}{N}$$

Where N_s is the total number of intervals out of N that the demand was met.

(ii) Volume-based Reliability (R_{volume}): Proportion of the total volume of water which was actually supplied divided by the total volume of water in demand in a time period:

$$R_{volume} = \sum_{t=1}^{N} D'_t / \sum_{t=1}^{N} D_t \, , D'_t \leq D_t$$

(iii) Resilience (∅): A quantitative measure to estimate the ability of a reservoir to recover from failure:

$$\emptyset = \frac{1}{\left(\frac{f_d}{f_s}\right)} = \left(\frac{f_s}{f_d}\right); 0 < \emptyset \leq 1$$

Where f_d denotes the total duration of the failures, i.e. $f_d = N - N_s$ and f_s denotes the continuous sequences of failure periods.

(iv) Vulnerability (η): Ratio of average shortfall to the average demand in a given duration:

$$\eta = \frac{\sum_{t=1}^{f_d} [D_t - D'_t / D_t]}{f_d}$$

(v) Sustainability (γ): Integrates all the defined indices mentioned above:

$$\gamma = \left(R_t \emptyset (1 - \eta)\right)^{1/3}$$

4. Results and Discussion

4.1 Performance of designed Pareto optimal operation polices

The six state-of-the-art methods were used to develop optimal reservoir operation policies for two competing objectives of irrigation discharge (m^3/s) vs flood control (m). The performance of different sets of pareto-optimal reservoir operation polices implemented using different methods has been represented in Figure 6. Arrows in Figure 6. indicates the direction of preference of the optimal operation solutions (ideal solution will most likely be in the bottom left corner).

The simulation results indicates that DDP outperforms the other models in obtaining pareto-optimal reservoir operation solutions. While the reservoir operation solutions developed using DDP showed the best performance, ISO was observed to have the least performance comparatively. The optimal operation solution obtained through DDP suggested an Irrigation release of 342.5 m^3/s with a flood control storage of 2.25 m (below 425 m). The better performance of DDP can be attributed to the fact that DDP works on the assumption that future inflows are deterministic (known), while, the uncertainty associated with inflows in the other methods affect the overall performance (Bertsekas 2000; Giuliani et al. 2016). Following DDP, the reservoir operation solutions derived through MPC and FQI showed better performance and had similar concave curve. This could be attributed to the fact that, MPC with its edge as a real-time approach overcomes the curses of dimensionality and modeling in DP by searching the optimal decisions over a series of horizon, avoids the computation of value function and uses the additional information at each time step to make better informed decision of operations (Morari and Lee 1999; Mayne et al. 2011). Next, FQI as a batch-mode reinforcement learning method, uses the experience from historic observations and model simulations to adopt a coarse discretisation of state control space to condition the state variables in this study thus overcoming the dimensionality and modeling curses in DP results (Castelletti et al. 2012; Feldbrugge 2010). The optimal operation solutions obtained by MPC and FQI suggested a release of 365.34 m^3/s and 418.9 m^3/s for irrigation with a corresponding flood control of 2.4 m and 2.34 m, respectively. The optimal operation solutions derived through SDP and SSDP (developed based on SDP) showed inferior performance (following ISO) than the other models used in the study. The reason for the inhibited performance of SDP could be due to the limitation of DP curses of dimensionality, modeling and competing multi-objectives (Powell 2007; Dobson et al. 2019), however, in the current study this curse is overcome by DDP since the assumption of deterministic knowledge of inflows looks to outweigh the limitations of the model in obtaining the optimal reservoir operation solutions. However, it is worth noting that DDP results cannot be always relied since there always some significant bias in the operation polices obtained thorough it (Hargreaves and Hobbs 2012).

One interesting observation is that, all the six models showed slightly varying operation solutions (with an exception of DDP and SDP in the irrigation objective end and ISO and FQI in the flood control end) when optimizing single objectives (in case of both irrigation and flood control) with the difference in operation policies in the magnitude of about 100 m^3/s between DDP and ISO for irrigation release and 0.3 m variations in flood control between DDP and MPC. However, in a similar study for a small reservoir system called Lake Como, Italy, Giuliani et al. (2016) observed that the difference in performance between the optimal reservoir operations developed using different models to be insignificant especially when optimizing single objectives. Additionally, from Figure 6. we can also clearly observe that there are distortions in the concave curve in the middle of the trade-off curve especially in the performance of SDP and SSDP. Obtaining concavity and good coverage of the whole trade-off curve has been challenging although we have only considered reservoir operation under two competing objectives. The performance of any single model used for modeling Pareto-optimal operation solutions for Pong seems to be limited and hence the optimal-operation solutions obtained from a combination of these methods needs to be considered before making real-life operation decisions.

4.2 Computation costs

The convergence time for deriving optimal reservoir operations of the six methods are presented in Table 4. The convergence time of the DP models were comparatively lower than that of the metaheuristic methods (ISO, MPC and FQI). As expected, due to the deterministic knowledge of inflows the convergence time was least in DDP with 3.69 minutes. The highest convergence time was observed in ISO followed by FQI with 7.45 and 7.25 minutes approximately. SSDP model's convergence time (4.37 minutes) has been observed to be better than SDP's (6.80) which could be attributed to the fact that SSDP model structure is an improvement on the SDP model framework (Côté and Arsenault 2019). The presented computational costs (convergence time) can only provide insight on the rough computation costs required for the different models to obtain optimal reservoir operation solution. It is important to note that the computational cost will increase multi-fold as the complexity of the reservoir operation objectives increases, for example, including drinking water supply and hydropower generation into the modeling objective will increase the computation costs drastically. Additionally, the convergence time of only the optimal model for each method is presented here, since the convergence time varies for each method with varying model specific parameters and simulations.

4.3 Reservoir Performance

Table 5 summarises the performance of the Pong Reservoir in three intervals 1998-2000, 2003-2005 and 2008-2010 (study period). Positive trend has been observed in time-based reliability value from 1998-2000 to the study period (increased from 0.22 to 0.38). Volume based reliability however, has decreased from 0.99 in 1998-2000 to 0.86 in 2008-2010. A slight decrease in vulnerability was observed from 1998-2000 to 2008-2010, however the value of the vulnerability index was high with ~0.65 throughout the three-time intervals. Resilience index of Pong is found to very low and decreasing from 0.11 to 0.09 from 1998-2000 to 2008-2010. Sustainability index which is a combined measure of all other performance indices suggests that the overall reservoir performance has slightly increased with sustainability index values increasing from 0.21 in 1998-2000 to 0.23 in 2008-2010. The results of the reservoir performance indices suggest that, though the overall performance (sustainability index) of Pong is increasing, the absolute value of the increase is still low. Key performance variables such as the resilience (decreasing and only in ~0.1 range) and vulnerability (high, in ~0.65 range) of Pong is degrading and the effective use of state-of-the-art reservoir operation models might be crucial in improving the overall performance of Pong, especially with changing climate with uncertain inflows.

5. Conclusion

In this study, six different state-of-the-art techniques were used to model optimal operation policies for a multi-purpose water reservoir system. DP (both DDP and SDP) which is widely used for reservoir operation modeling although has several advantages such as the ease of modeling, robustness in the model structure (e.g. decision taken at a given time step in addition to affecting the next time step also affects the subsequent system state and costs), etc., it has several limitations for application in real-world conditions due to the challenges of dimensionality, modeling and multiple objective curses. Some limitations in DP are overcome by the other state-of-the-art techniques. For example, ISO develops a set of variables to condition the operation policies obtained to get superior results, although it uses the release decisions determined by DDP. SSDP uses multiple scenarios of reservoir inflows (streamflow) as empirical distribution variabilities unlike the explicit probabilistic description of system disturbances used in SDP. The pareto-optimal front of all the six proposed modeling techniques were determined for the Pong Reservoir system in India for two competing decision objectives of irrigation and flood control. The performance of the solutions in the pareto-optimal front suggests that the DDP, without any surprise, shows better performance since it assumes the deterministic knowledge of future inflows. When optimizing a single objective, all the six methods showed similar performance (Refer the extremes of the Pareto front in Figure 6) for both irrigation and flood control objectives, and the convergence could not be obtained over the entire trade-off curve. Of the novel techniques used in the study, MPC and FQI showed best performance. This could be attributed to the unique characteristics and advantages of both these models. Though the performance of metaheuristic models such as the MPC and FQI is better than the DP models (except DDP) the computational costs however is much lower in DP models than in the metaheuristic models. The performance of the Pong reservoir operation was assessed by estimating the reservoir performance indices such as resilience, reliability (volume and time), vulnerability and sustainability. Performance indices suggest that the overall performance of the reservoir is showing a positive trend. However, the performance of some key indices such as the resilience and vulnerability of Pong is not positive. The study demonstrates that, the development of optimal operation policies using state-of-the-art modeling techniques and collectively using the operation solutions of different models for decision making might be crucial in the optimal management of reservoir systems similar to Pong, especially under increasing vulnerability and decreasing resilience of reservoir systems in effectively managing the demand under climate change risks. More comprehensive modeling studies comparing the performance of different reservoir operation models needs to be carried out under real-world operations especially at varying hydro-geo-climatic conditions to improve the planning and management of water resource systems.

Declarations

Competing Interests:

The authors declare there is no competing interests pertaining to this work.

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Tables

Table 1. An overview of recent optimal reservoir operation studies.

Literature (Authors)	Study area and climate type	Objectives	Models / Techniques used	Results
Li et al. (2017)	Danjingkou Reservoir, China; Subtropical monsoon climate	Determination of minimum ecological water demand; Multi-objective optimization model development based on the GP method; Generation of reservoir operation polices	Goal programming based Improved Multi-Objective Optimization Model (IMOOM-GP)	Danjiangkou Reservoir's regulation and storage capacity improved. The results suggested that in addition to flood control priority, operation priority of Danjiangkou Reservoir would change in the future to include other objectives including downstream water security and ecological water supply.
Liu et al. (2017)	Three Gorges Reservoir, China; Sub-tropical monsoon climate	Develop a multi-objective operation model to estimate the spillway's optimal operation of using POA; Abstract the optimal real-time operation using SSVM	Smooth support vector machine (SSVM) model; Progressive optimality algorithm (POA)	Most reasonable results are developed by optimizing the number and order of spillways. SSVM model shows promise in generating short term or real-time reservoir operation polices. Flood risk can be reduced and hydropower generation can be improved during the flood season by using SSVM model.
Khorshidi et al. (2019)	Dorudzan Reservior; Iran; Hot semi-dessert climate	Optimum operation policy (12-month) is developed under future potential dry periods; Optimize the storage loss and maximize the allocation of water to agricultural release of CVR as leader's objective	Conditional Value at Risk (CVR) based Leader-Follower game multi-objective optimization model (LFG)	The LFG model demonstrates the ability to keep the associated risks in the developed operation polices within an acceptable range at the same time satisfy the demand supply.
Srinivasan and Kumar (2018)	Dharoi reservoir, India; Hot Semi-arid climate	Minimize the total shortage ratio and the maximum storage	Structured piecewise linear-hedging rule with multi-objective Simulation	Improvement in the computational efficiency and the Pareto-optimality

			Optimization (S_o) framework; Non-dominated sorting genetic algorithm based on evolutionary search	is illustrated with Dharoi reservoir, operation. S-O framework along with the parameterized piecewise linear hedging rule developed may be extrapolated to any multi-purpose reservoir system operations.
Yaseen et al. (2019)	Golestan and Voshmgir Reservoirs, Iran; Cold semi-arid climate with continental climate characteristics	Improve the reservoir optimization by implementing PSO in parallel to the suboptimal operation solutions generated by BA	Hybrid bat–swarm algorithm (SA-HB) based on particle swarm optimization (PSO) and bat algorithm (BA)	SA-HB hybrid algorithm achieves minimum irrigation deficits by optimizing reservoir operations. Using SA-HB reduces the computational time required in the convergence procedure.
Yang et al. (2019)	Hongjiadu and Qingjiang Reservoirs, China; Humid Sub-tropical climate	Optimize the scheduling scheme for multi-objective flood control and, ecological and water supply operation in Hongjiadu reservoir and Qingjiang cascade reservoirs respectively	Improved multi-objective particle swarm (IMOPS) optimization based on grey correlation analysis and technique for order preference by similarity to an ideal solution (GCA-TOPSIS)	GCA-TOPSIS efficiently evaluates and finds the most suitable policy under different decision making scenarios. GCA-TOPSIS provides strong evidence for the implementing balanced scheduling decisions under multi-objective operations in complex reservoir operations.
Kong, et al. (2021)	Three Gorges Reservoir, China; Sub-tropical monsoon climate	Select the optimal solution from a set of Multi-Objective reservoir operation policies in the Pareto-optimal front	Clustering-based method for solution selection (CMSS) with MeiWang fluctuation similarity measure (MwFSM)	MwFSM effectively distinguishes reservoir operation process. The CMSS selects solutions from a large Pareto set since it can extract additional information in the decision space.
Yang, et al. (2019)	Chao Phraya Reservoir, Thailand; Tropical climate	Apply RNN to simulate reservoir operations under regulation of multiannual flow; explore the RNN models suitability for the operation of reservoir under extreme flood and drought events	The recurrent neural networks (RNN) such as Nonlinear autoregressive models with exogenous input (NARE), Long short-term memory (LSTM) and genetic algorithm based NAXE (GA-NAXE)	GA-NAXE produces the most accurate reservoir simulation among the RNNs and is highly stable than NARE. GA-NAXE model results are effective under extreme events (e.g. floods). Real time reservoir operations model developed by ensemble GA-NAXE and hydrological models

				produced the best operational solutions.
Zang et al. (2018)	Gezhouba Reservoir, China; sub-tropical monsoon climate	Simulate the operation policies for the reservoir at different time scales (e.g. daily and monthly) using historic reservoir operation data and AI techniques	Long short-term memory (LSTM) technique, Support vector regression (SVR) and backpropagation neural network (BPNN)	Results suggest that LSTM, SVR and BPNN are effective in making reservoir operation decisions. BPNN and SVR are more suitable to model operation policies of reservoir even with limited data while LSTM are more effective in modeling under low-flow conditions.
Asadieh and Afshar (2019)	Dez reservoir, Iran; Hot and humid climate	Optimize reservoir operation problem using CSS optimization algorithm and compare its performance with other optimization methods.	Charged System Search (CSS) metaheuristic algorithm	Robustness and supremacy of CSS algorithm to solve reservoir operation problems for longer time frame is established compared to alternative methods such as particle swarm optimization.
Saadat and Asghari (2017)	Zayandehrud Reservoir, Iran; Cold dessert climate	Improve the traditional stochastic dynamic Programming model's accuracy by improving the accuracy of steady state operating policies	Reliability Improved Stochastic Dynamic Programming model (RISDP)	Using RISDP operating policies for real-life reservoir system indicates improvement in objective function value by 15%.
Samadi-koucheksaraee et al. (2019)	Khersan-1 and the Dez reservoirs, Iran; Hot and humid climate	Compare the solutions determined with GE algorithm with genetic algorithm (GA), linear programming (LP) and non-linear programming (NLP)	Gradient Evolution (GE) algorithm	Results demonstrate the superior ability of GE to model optimal reservoir operation policies.
Ehteram et al. (2017)	Bazoft reservoir, Iran; Hot humid continental climate	Investigate the potential of shark algorithm in optimization of optimum reservoir operations; Compare the performance of shark algorithm with particle swarm optimization and genetic algorithm.	Shark algorithm	Shark algorithm indicates superiority by outperforming other optimization algorithms and achieves lower vulnerability index and higher reliability index.
Sun et al. (2018)	Huangjinxia reservoir, China; Sub-tropical climate	Use MOEA/D-AWA for optimization of reservoir operation problem; Determine the performance by comparing with other algorithms based on hyper-volume index	Multi-objective evolutionary algorithm developed with decomposition and adaptive weight vector adjustment (MOEA/D-AWA)	The MOEA/D-AWA is reasonable and effective and can be applied for multi-objective reservoir operation modeling.
Zhang et al. (2018)	Ankang reservoir, China;	Develop bi-objective model to optimize flood control objective	The multi-objective evolutionary algorithm based on differential	Results on flood observations (experimental) indicates

	Subtropical climate		evolution decomposition (MOEA/D-DE)	that the MOEA/D-DE algorithm outperforms other comparable algorithms and increased the dam safety by reducing flood peak.

Table 2: Salient features of Pong Reservoir (Note: All the levels are mentioned as reduced level)

Characteristics	Quantity
Surface area (km^2)	240, and 450 during floods
Catchment Area ($km^{2)}$	12,561
Max. width (Km)	2
Max. length (Km)	42
Water volume (Mm^3)	8,570
Surface elevation (m)	436
Max. depth (m)	97.8
Dead storage level (m)	384
Minimum reservoir level (m)	389
Maximum reservoir level (m)	425
Gross storage capacity (Mm^3)	8,570
Live storage (Mm^3)	7,290
Dead storage (Mm^3)	1,280

Table 3: Weight combination for aggregation of objectives

Combination	Flooding	Irrigation
1	1.0	0
2	0.75	0.25
3	0.5	0.5
4	0.35	0.65
5	0.2	0.8
6	0.1	0.9
7	0	1.0

Table 4: Convergence time for obtaining optimal reservoir operation policies (Note: Convergence time might increase or decrease with varying computation capacity)

Method	Elapsed time (minutes)
Deterministic Dynamic Programming	3.69
Stochastic Dynamic Programming	6.80

Implicit Stochastic Optimization	7.45
Fitted Q-Iteration	7.25
Sampling Stochastic Dynamic Programming	4.37
Model Predictive Control	6.68

Table 5: Reservoir Performance

Performance Index	1998-2000	2003-2005	2008-2010
Time Based Reliability	0.22	0.29	0.38
Volume Based reliability	0.99	0.92	0.86
Resilience	0.11	0.10	0.09
Vulnerability	0.66	0.65	0.64
Sustainability index	0.21	0.22	0.23

Figures

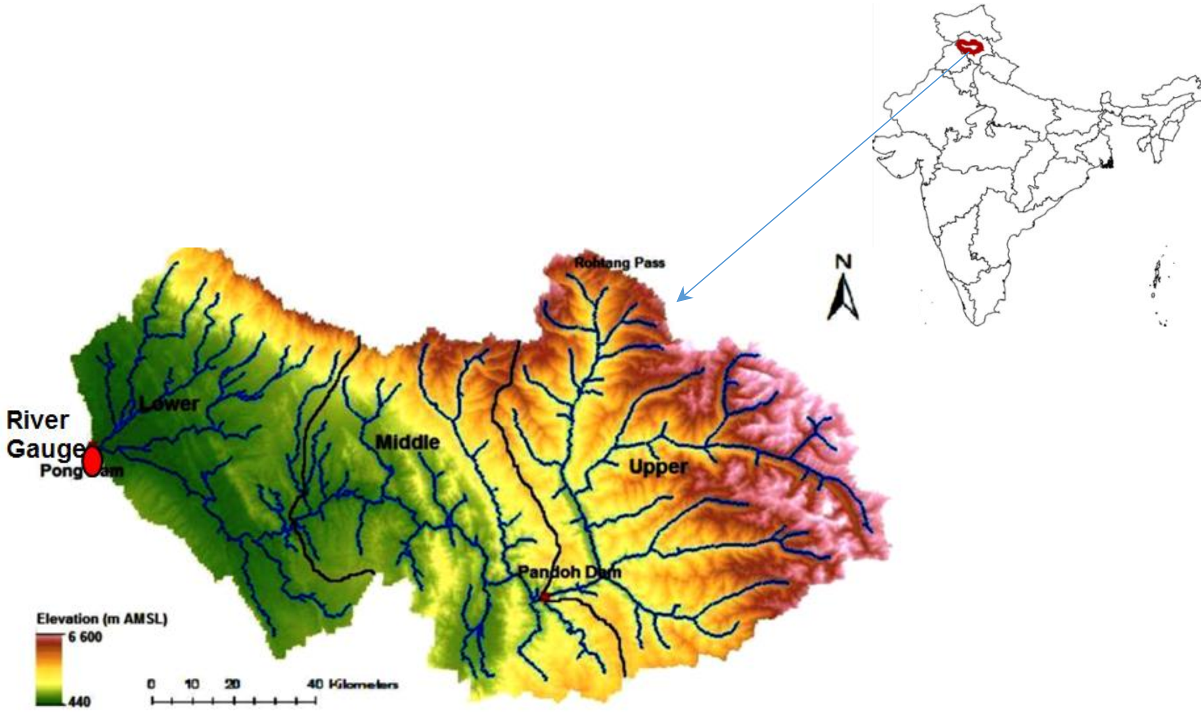

Figure 1: Study area Plot

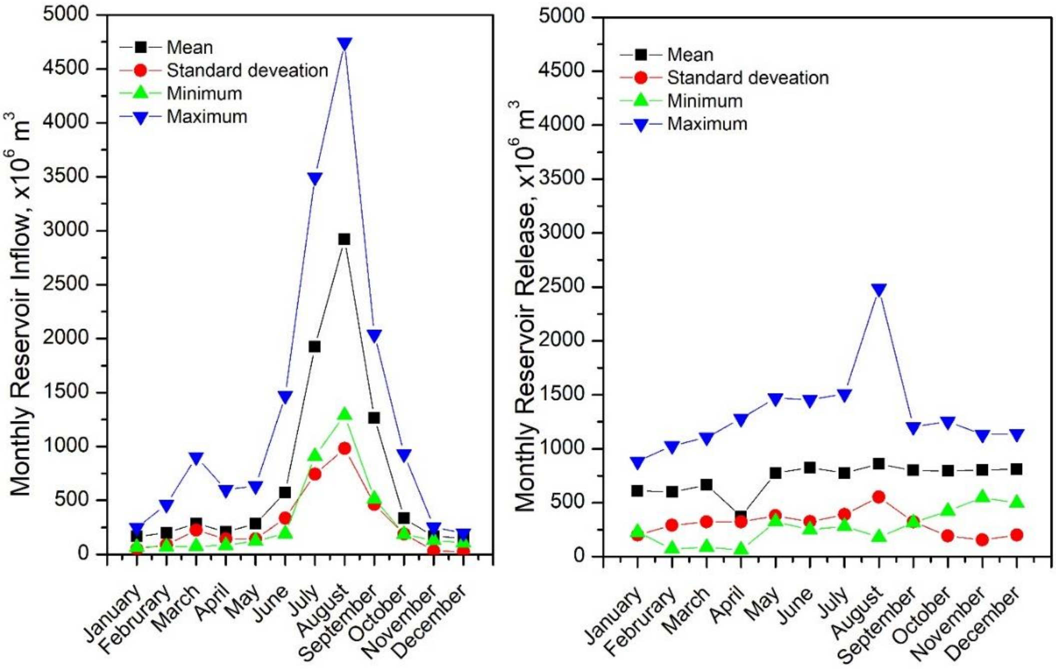

Figure 2: Monthly average of reservoir inflow and release (1998-2012)

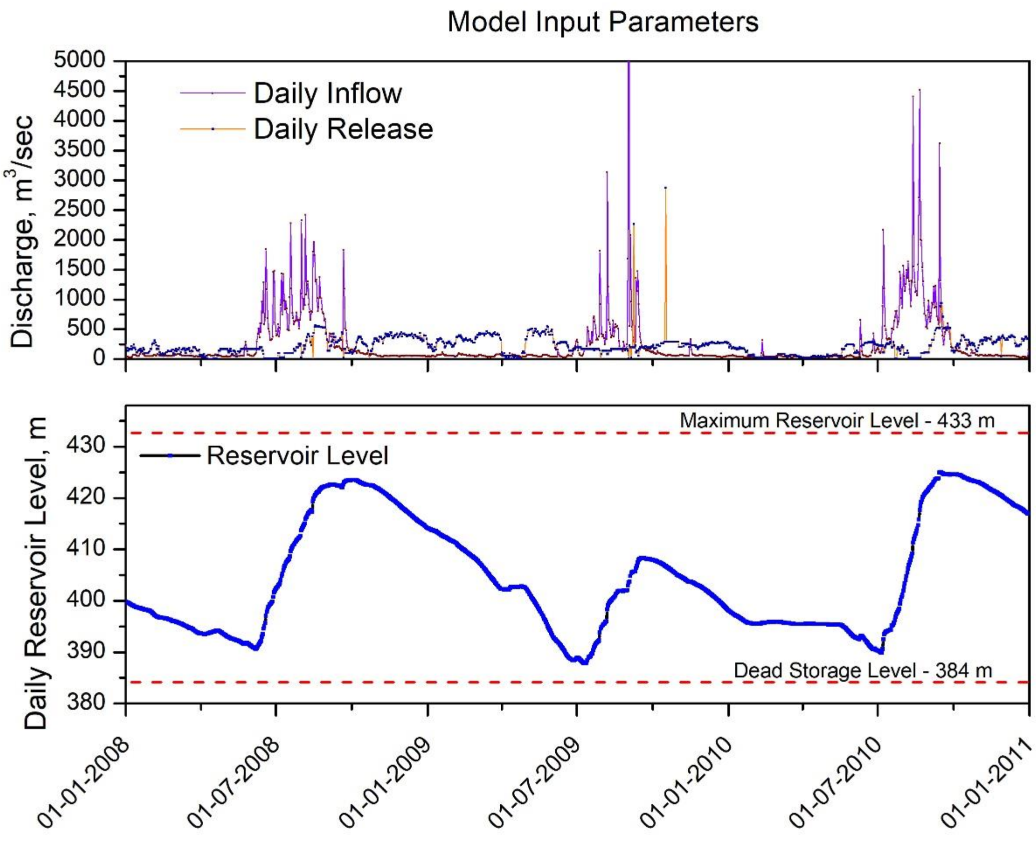

Figure 3: Model inputs: Time series of Inflow, release and reservoir level (2008-2011)

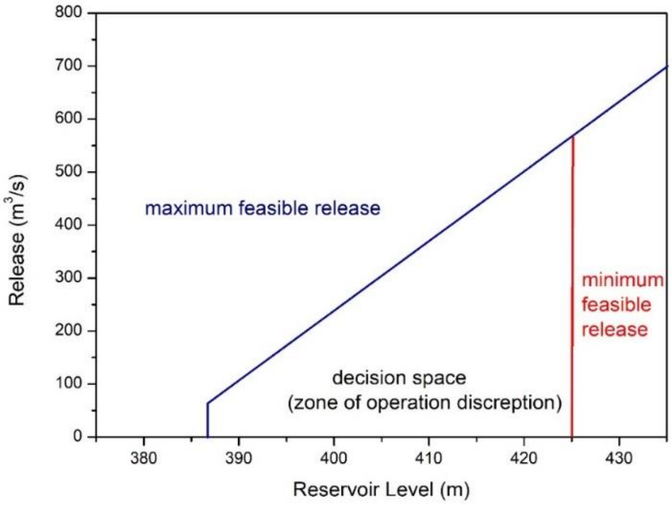

Figure 4: Zone of operation discretion for the Pong Reservoir confined by the minimum and maximum feasible release functions

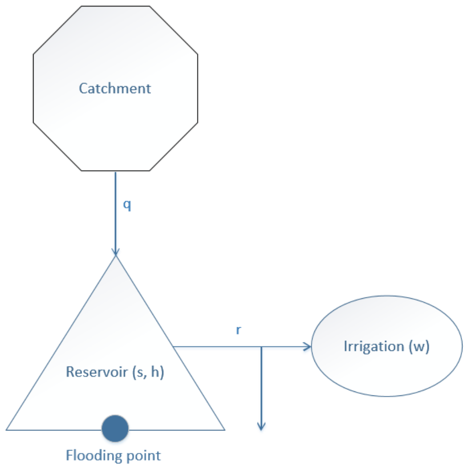

Figure 5: Representation of the scheme of Pong Reservoir system used for modelling (notations: h- reservoir level, s-water storage in reservoir, q-inflow in the upstream and w-irrigation water demand)

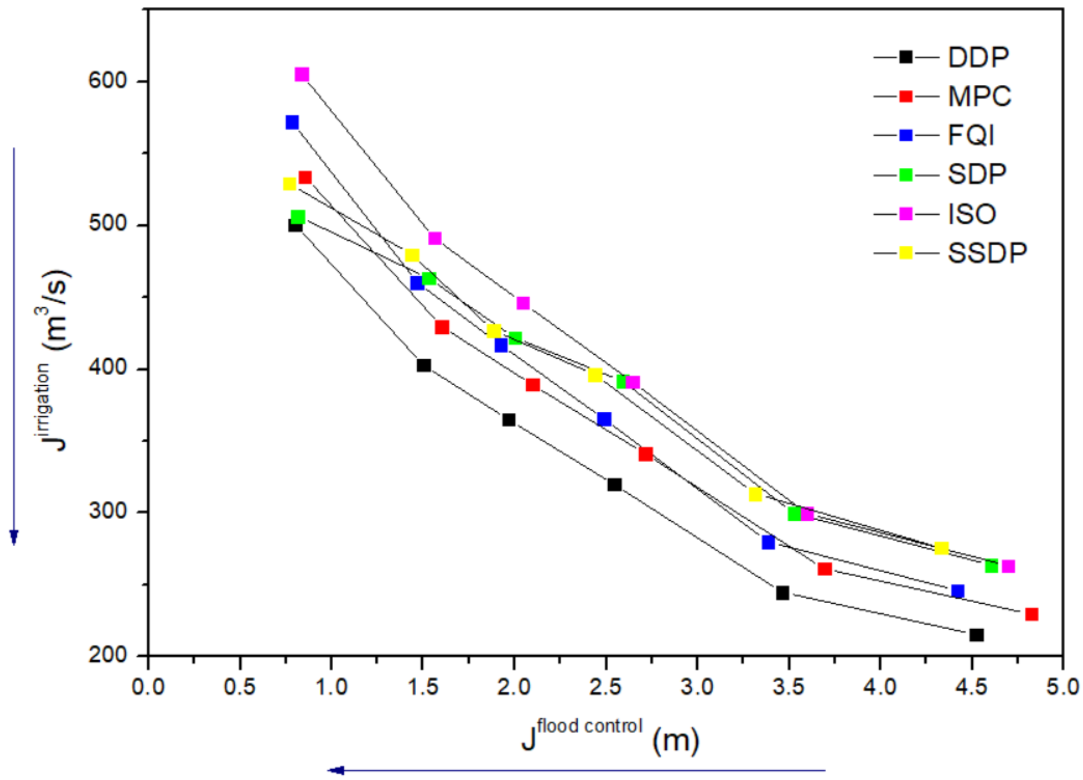

Figure 6: Performance of the different sets of Pareto optimal reservoir operation solutions designed through implementing the state-of-the-art methods