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Multi-Objective Modeling Framework for Environmental Flow Optimization in a River-Reservoir System Using Histogram Comparison Approach for Estimation of Hydrologic Alteration

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Abstract
In the proposed Parameterization-Simulation-Optimization (P-S-O) framework for multi-objective E-flow optimization for long-term planning of reservoir operation, Histogram Comparison Approach (HCA) is adopted for the estimation of Hydrologic Alteration (HA) and the resulting performance is compared with that of Range of Variability Approach (RVA) in terms of the trade-off solutions obtained, optimal monthly E-flow targets and the individual alterations achieved in the river. A limiting constraint on the maximum average monthly E-flow deficits is included in the formulation in order to ensure realistic optimal E-flow targets at the reservoir level. The parameterization of the reservoir operation rules includes rule curves concerning carryover storage, Irrigation, E-flows and their transitions and fuzzified hedging factors as the decision variables with monthly water availability as the hedging trigger. The E-flow targets are derived as fractions of the respective mean monthly flows for the three hydrologic year types (dry, normal and wet), accounting for the intra- and the inter-annual flow variability. The meta-heuristic Borg-MOEA is employed as the search engine in the framework. The highly regulated Bhadra reservoir in Southern India is employed as the application case example. The individual alterations of the various hydrologic indicators appear to be reasonable for all the solutions along the P-O front of HCA, thus establishing its reliability in estimating HA and consequently the optimal E-flow targets derived and the reservoir operating policy. While, the RVA underestimates the individual alterations due to which the HA estimate, the optimal E-flow targets derived and the reservoir operating policy may not be reliable.

Keywords Environmental flow optimization · Histogram comparison approach · Fuzzy-rule-based hedging strategy · Multi-purpose reservoir operation · Modified shortage index · Borg multi-objective evolutionary algorithm

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1 Introduction

With the increasing importance of maintaining the health of the river ecosystem, adopting appropriate environmental flow assessment (EFA) methods to evaluate the effects of reservoir regulation on the river ecosystem health and modifying the existing long-term reservoir operation strategies to arrive at reasonable trade-off between E-flow requirements and human needs becomes necessary. The EFA methods proposed over the last three decades have been classified by Tharme (2003) as hydrologic, hydraulic, habitat simulation and holistic. Hydraulic and habitat simulation methods require information regarding stream channel characteristics and physical habitat metrics, while holistic methods would require detailed data base and a multi-disciplinary team of experts (Verma et al. 2023). In the absence of such detailed information and a multi-disciplinary team of experts, hydrological methods yield reliable environmental flow (E-flow) estimates, and hence hydrologic alteration due to dam operation is considered as a surrogate for tracking the health of downstream river ecosystem. Quantifying hydrologic regime alteration due to such regulation involves comparative assessment of hydrologic metrics (Shiau and Wu 2013; Vogel et al. 2007; Gao et al. 2012) or hydrologic statistics (such as magnitude, frequency, duration, timing and rate of change) corresponding to inflows and releases. In this regard, Indicators of Hydrologic Alteration and Range of Variability Approach (IHA-RVA) (Richter et al. 1996, 1998) seems to be the most popular one, especially in the context of E-flow optimization in river-reservoir systems due to its simplicity, interpretability, and a well-defined simulation framework. Shiau and Wu (2007) have used all the 32 Indicators of Hydrologic Alteration (IHA) to estimate HA, while Yin et al. (2011) employed selected IHA, and Li et al. (2018) employed a reduced set of IHA, using Principal Component Analysis (PCA).

However, the RVA has a number of limitations, such as considering only the frequency of each IHA within the specified target range, but ignoring the variability even within this range, and not accounting the alteration in the frequency as well as the variability beyond the target range (Shiau and Wu 2008) and those related to hydrologic year type (HYT) (Huang et al., 2017), thus resulting in the underestimation of the flow regime alteration. Although a few modifications to IHA-RVA have been proposed in the literature (Shi et al. 2019; Zheng et al. 2021), they have not been adopted in E-flow optimization studies. The limitations of RVA were addressed in the Histogram Matching Approach (HMA) proposed by Shiau and Wu (2008) using histogram dissimilarity index to assess the flow regime alteration, accounting for the variation in frequency and variability of the hydrologic indicators through class-to-class and cross-class correspondence. In the context of E-flow optimization in reservoir operation for obtaining the trade-off between HA and shortage ratio of water supply, HMA outperforms RVA in the preservation of the natural flow variability. Subsequently, Huang et al. (2017) identified two limitations of HMA and proposed the Histogram Comparison Approach (HCA) addressing the above limitations, and showed that it could produce more accurate and effective estimates of HA over RVA and HMA, but in a simulation setting. Although HCA is an accurate and rational method of HA estimation, its use in the context of reservoir E-flow optimization has not been reported so far. In the multi-objective E-flow optimization formulation proposed in the current research work, HCA is adopted for the estimation of HA and the resulting performance is compared with that of RVA in terms of the trade-off obtained, optimal monthly E-flow targets and release policies derived at the reservoir, and the individual alterations achieved in the river through a post-optimal analysis.

In the context of E-flow optimization studies dealing with reservoir operation, several works (Guo et al. 2018; Lei et al. 2023) have adopted fixed E-flow targets. While, a number of research works (Li et al. 2018; Yan et al. 2021; Sedighkia and Abdoli 2022; Yazdian et al. 2024) have directly optimized E-flow releases from the reservoir without specifying the targets. On the other hand, several of the other multi-objective E-flow optimization studies dealing with reservoir operation (Shiau and Wu 2007, 2013; Yin et al. 2010; Yin and Yang 2011) employ minimizing the HA as well as the deficit indices of other beneficial uses as the two objectives, while deriving the optimal E-flow targets and the optimal reservoir release policies.

These multi-objective formulations aim to obtain the possible range of HA and the corresponding E-flow targets for the river-reservoir system considered. However, the objective function "$Minimize\ HA$", introduced as a surrogate for checking the health of the river ecosystem, by itself, does not regulate the deficits in E-flow releases from the reservoir, corresponding to the derived optimal E-flow targets. This issue has not been addressed in the earlier research works. Hence, a constraint on monthly E-flow deficits is introduced at the reservoir level in the multi-objective formulation proposed in this research work, so that the derived E-flow targets would be realistic for implementation.

Several of the existing E-flow optimization studies have employed discrete hedging strategy for reservoir operation. The limitation concerning sharp changes in releases between storage zones in discrete hedging strategy was overcome by Ahmadianfar et al. (2016) by introducing transition rule curves (TRCs) and fuzzification of hedging factors, which was endorsed by Shiau et al. (2018). However, both these works have employed reservoir storage/water level as the hedging trigger, while the state of inflows was not considered; also, the release targets and the upper rule curve were prefixed and not included as decision variables. These two limitations have been addressed in the current research work.

A novel multi-objective (M-O) parameterization-simulation-optimization (P-S-O) framework for long-term monthly reservoir operation is proposed in this research work, in which optimal monthly E-flow targets are derived by employing "minimize MSI of Irrigation (beneficial need)" and "minimize hydrologic alteration (HA)" as the two conflicting objective functions, with the monthly Irrigation targets being pre-specified. The contributions of this research work are as follows: (i) Employing Histogram Comparison Approach (HCA) for the estimation of hydrologic alteration (HA) in the proposed multi-objective E-flow optimization model; (ii) Evaluating the merits of using the HCA for HA estimation in the context of E-flow optimization in a river-reservoir system over the popular Range of Variability Approach (RVA); (iii) Inclusion of a limiting constraint on the maximum average monthly E-flow deficit at the reservoir to ensure realistic and implementable optimal E-flow targets at the reservoir level; (iv) Fuzzy rule curve based hedging strategy proposed herein aims to address two of the limitations of the model proposed by Ahmadianfar et al. (2016) by means of: (a) implementing "monthly water availability (initial reservoir storage + inflows)" as the hedging trigger (similar to that of Srinivasan and Kumar (2018) for single purpose water supply operation) and (b) including the monthly upper rule curve parameters (carryover storage targets) also as decision variables into the proposed P-S-O framework.

The other features of the framework are as follows. In both the HA estimation approaches (HCA and RVA) adopted, a reduced set of indicators are chosen from the 32 IHA proposed by Richter et al. (1996) by employing Principal Component Analysis (PCA). In order to capture the influence of the intra-annual as well as the inter-annual flow variability, the optimal E-flow targets are derived as fractions of the respective mean monthly flows (MMF) for the three hydrologic year types (HYTs) (dry, normal and wet), separately. The direct policy search (DPS) technique (Giuliani et al. 2016), also referred to as the parameterization-simulation-optimization approach (Koutsoyiannis and Economou 2003), is adopted for deriving the long-term reservoir operation strategy, in which the robust Borg Multi-Objective Evolutionary Algorithm (MOEA) (Hadka and Reed 2013) is employed as the search engine, which has the ability to select the appropriate recombination operators, and improved features such as, ε-box dominance archive, enhanced computational speed and rate of convergence. The efficacy of the proposed P-S-O framework is demonstrated through the operation of the southwest monsoon-fed multi-purpose reservoir Bhadra in Southern India, wherein well-defined policies for E-flow releases do not seem to exist.

2 Model Development

2.1 Optimization Model

The multi-objective formulation that presents the trade-off between the MSI computed with regard to the pre-specified monthly irrigation demands and the HA in the river just downstream of the reservoir, herein denoted as IMHA is given as.

$$Z_1 = Minimize\ MSI_{IR} = \frac{100}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\frac{R_{IR,j}^{T} - R_{IR,i,j}}{R_{IR,j}^{T}}\right)^2 \tag{1a}$$

$$\text{and } Z_2 = Minimize\ HA = \left(\frac{1}{G}\sum_{m=1}^{G} D_m^2\right)^{1/2} \tag{1b}$$

where, D_m is the hydrologic alteration of the individual indicator estimated using HCA or RVA, in which *m=1,2,....,G* denotes the number of Indicators of Hydrologic Alteration (IHA).

The constraints (2)-(5) represent the reservoir storage-continuity equations, the upper and the lower bounds on storage and the upper bound of releases, respectively.

$$S_{i,j+1} = S_{i,j} + I_{i,j} - R_{IR,i,j} - R_{ER,i,j} - E_{i,j} - Sp_{i,j}\ \ \forall i,j \tag{2}$$

$$S_{min} \le S_{i,j} \le S_{cap}\ \ \forall_{i,j} \tag{3}$$

where S_{min} is the dead storage, S_{cap} is the reservoir capacity at full reservoir level (FRL), $S_{i,j}$ and $S_{i,j+1}$are the initial and the end storages in the reservoir; $I_{i,j}$ is the inflow into the reservoir; $E_{i,j}$, $Sp_{i,j}$, $R_{IR,i,j}$ and $R_{ER,i,j}$ are respectively the evaporation loss, the spill, the releases for Irrigation and E-flow from the reservoir during year i and month j.

The releases towards Irrigation and E-flow requirements are constrained by the respective targets as:

$$R_{IR,i,j} \leq R^{T}_{IR,j} \ \ \forall i,j \tag{4}$$

$$R_{ER,i,j} - R^{T}_{ER,k,j} \leq 0 \ \ \forall i,j \tag{5}$$

where $R^{T}_{ER,k,j} = Eff_{k,j} \times Q_j \ \ \forall_{k,j}$

in which k denotes the hydrologic year type (HYT) and Q_j denotes the mean monthly flow of the month j. In Eq. (5), monthly varying E-flow release targets, $R^{T}_{ER,k,j}$ are parameterized using monthly varying E-flow fractions $(Eff_{k,j})$ which vary depending on the HYT, but do not vary within the same HYT. It is to be noted that both $R_{ER,i,j}$ and $R^{T}_{ER,k,j}$ in Eq. (5) are unknowns.

A limiting constraint on the maximum average monthly E-flow deficit (Eq. 6) is included in order to derive realistic E-flow targets at the reservoir.

$$max_j \left\{ Def_{ER,j} \right\} \leq P_{ER} \ \ \forall_j \tag{6}$$

wherein, $Def_{ER,j} = \left\{ \frac{1}{M} \left(\sum_{i=1}^{M} \left(\frac{R^{T}_{ER,k,j} - R_{ER,i,j}}{R^{T}_{ER,k,j}} \right) \right) \times 100 \right\} \ \forall j$

in which $Def_{ER,j}$ denotes the average monthly deficit over M years, expressed as a percent of the monthly target demand; and P_{ER} is the specified upper limit of the maximum average monthly deficit (%).

2.2 Parameterization of Fuzzy-Rule-Based Hedging Strategy and Reservoir Simulation Model

The fuzzy-rule-based hedging strategy implements the "degree of belongingness" to the storage in each zone, using trapezoidal membership functions. The carry-over storage rule curve, referred as the upper rule curve (URC_j) is also optimized along with the rule curves for Irrigation and E-flows. Accordingly, the equations for deriving the transition rule curves are modified to ensure proper sequencing and appropriate shape of the storage rule curves and the transition rule curves (Fig. 1a). The maximum (S_{max}) and the minimum (S_{min}) storages in Fig. 1a correspond to the full reservoir level (FRL) and the dead storage level (DSL), respectively.

In order to reduce the number of rule curve decision variables, and to avoid the intersection or crossing of the rule curves, the Irrigation rule curve (IRC_j) is expressed as a fraction(f_1) of URC_j (Eq. 7a) and the E-flows rule curve (ERC_j), in turn, is expressed as a fraction (f_2) of IRC_j (Eq. 7b).

$$IRC_j = f_1 \times URC_j \tag{7a}$$

$$ERC_j = f_2 \times IRC_j \tag{7b}$$

The two rule curves, IRC_j and ERC_j that divide the storage space into three zones, the upper and the lower boundaries of the transition zones 1–2 and 2–3, and zone-4 (between URC_j and S_{max}) are shown in Fig. 1a. The membership fractions of each transition rule curve (TRC_j) in the three zones are shown in Fig. 1b. This formulation can be easily extended to more number of purposes.

The modified transition rule curve equations (8a) to (8d) are presented below.

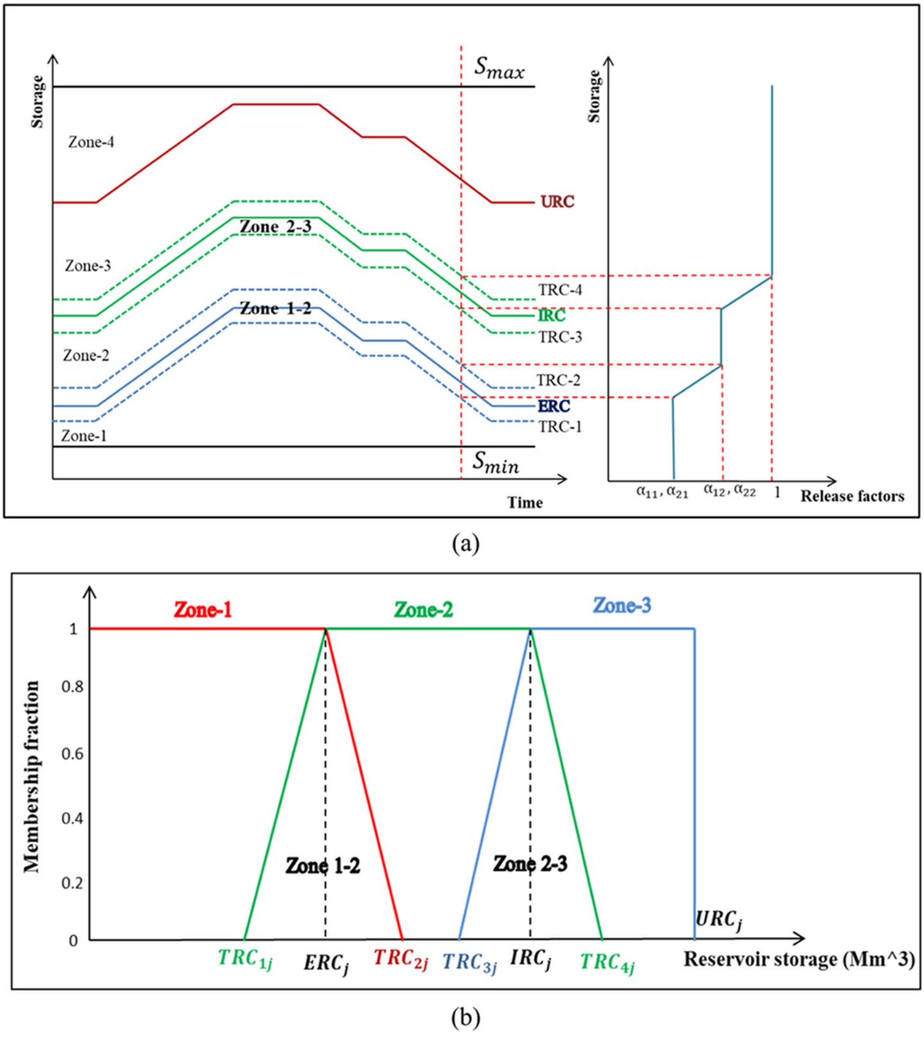

Fig. 1 **a** Storage Rule Curves (URC_j, IRC_j & ERC_j), Transition rule curves (TRC_{1j}, TRC_{2j}, TRC_{3j} & TRC_{4j}) and corresponding release factors α_{11}, α_{12} of Irrigation and α_{21}, α_{22} of E-flows (**b**) Membership fractions of each Transition Rule Curve (TRC_j) in the three zones using Trapezoidal membership functions

$$TRC_{4j} = IRC_j + \beta_1(URC_j - IRC_j) \tag{8a}$$

$$TRC_{3j} = IRC_j - \beta_2(IRC_j - ERC_j) \tag{8b}$$

$$TRC_{2j} = ERC_j + \beta_3(TRC_{3j} - ERC_j) \tag{8c}$$

$$TRC_{1j} = S_{min} + \beta_4(ERC_j - S_{min}) \tag{8d}$$

where β_1, β_2, β_3 and β_4 are the transition rule curve parameters (0<β_1, β_2, β_3 and β_4<1), which form part of the decision vector and remain constant across months and years.

On defining the transition rule curves, the degree of belongingness of storage in each zone, in any month j, is given by Eqs. (9a) to (9c):

$$\mu_{3,i,j} = \begin{cases} 1 & S_{i,j} > IRC_j \\ \frac{S_{i,j}-TRC_{3j}}{IRC_j-TRC_{3j}} & TRC_{3j} < S_{i,j} \leq IRC_j \\ 0 & S_{i,j} \leq TRC_{3j} \end{cases} \tag{9a}$$

$$\mu_{2,i,j} = \begin{cases} 0 & S_{i,j} \leq TRC_{1j} \\ \frac{S_{i,j}-TRC_{1j}}{ERC_j-TRC_{1j}} & TRC_{1j} < S_{i,j} \leq ERC_j \\ 1 & ERC_j < S_{i,j} \leq IRC_j \\ \frac{TRC_{4j}-S_{i,j}}{TRC_{4j}-IRC_j} & IRC_j < S_{i,j} \leq TRC_{4j} \\ 0 & S_{i,j} > TRC_{4j} \end{cases} \tag{9b}$$

$$\mu_{1,i,j} = \begin{cases} 1 & S_{i,j} \leq ERC_j \\ \frac{TRC_{2j}-S_{i,j}}{TRC_{2j}-ERC_j} & ERC_j < S_{i,j} \leq TRC_{2j} \\ 0 & S_{i,j} > TRC_{2j} \end{cases} \tag{9c}$$

Since the storage may simultaneously belong to different zones with different membership values, the fuzzified release factor for each release is expressed as the weighted average release factor. Thus, the hedged release targets for Irrigation and E-flows are given by Eqs. (10a) and (10b), respectively:

$$RZ^T_{IR,i,j} = \left(\frac{\alpha_{11}\mu_{1j} + \alpha_{12}\mu_{2j} + \alpha_{13}\mu_{3j}}{\mu_{1j} + \mu_{2j} + \mu_{3j}} \right) * R^T_{IR,j} \tag{10a}$$

$$RZ^T_{ER,i,j} = \left(\frac{\alpha_{21}\mu_{1j} + \alpha_{22}\mu_{2j} + \alpha_{23}\mu_{3j}}{\mu_{1j} + \mu_{2j} + \mu_{3j}} \right) * R^T_{ER,k,j} \tag{10b}$$

where, the release factors in zone 3, $\alpha_{13} = \alpha_{23} = 1$ indicate "no hedging"; α_{11} and α_{12} are the release factors of Irrigation release in zone 1 and 2 respectively; α_{21} and $\alpha_{22}$are the release factors of E-flow release in zone 1 and 2, respectively, which form part of the decision vector and remain constant across months and years; however, the values of $RZ^T_{IR,i,j}$ and $RZ^T_{ER,i,j}$ vary with both year and month.

The water availability ($WA_{i,j}$) that is employed as the hedging trigger and the release rules based on water availability are given by equations (11) to (13):

$$WA_{i,j} = I_{i,j} + S_{i,j} - E_{i,j} \tag{11}$$

$$R_{ER,i,j} = \begin{cases} R^T_{ER,k,j} & WA_{i,j} > TRC_{4j} \\ RZ^T_{ER,i,j} & RZ^T_{ER,i,j} < WA_{i,j} \le TRC_{4j} \\ WA_{i,j} & 0 < WA_{i,j} \le RZ^T_{ER,i,j} \\ 0 & WA_{i,j} \le 0 \end{cases} \tag{12}$$

$$R_{IR,i,j} = \begin{cases} R^T_{IR,j} & WA_{i,j} > TRC_{4j} \\ Min\{(WA_{i,j} - RZ^T_{ER,i,j}),\ RZ^T_{IR,i,j}\} & RZ^T_{IR,i,j} < WA_{i,j} \le TRC_{4j} \\ (WA_{i,j} - RZ^T_{ER,i,j}) & RZ^T_{ER,i,j} < WA_{i,j} \le RZ^T_{IR,i,j} \\ 0 & WA_{i,j} \le RZ^T_{ER,i,j} \end{cases} \tag{13}$$

It is to be mentioned that the historical reservoir inflows only are used in the P-S-O framework, thus depicting a perfect forecast scenario.

Carryover storage and spill for year i and month j are then calculated using Eqs. (14) and (15), respectively.

$$S_{i,j+1} = Min\left\{(WA_{i,j} - R_{ER,i,j} - R_{IR,i,j}),\ S^T_j\right\} \tag{14}$$

$$Sp_{i,j} = Max\left\{\left(WA_{i,j} - R^T_{ER,k,j} - R^T_{IR,j} - S^T_j\right),\ 0\right\} \tag{15}$$

where S^T_j is the monthly carryover storage target for the month j, which does not vary across years.

It is to be mentioned that the optimization model for the reservoir operation works at a monthly time scale, while HA is evaluated through simulation at a daily time scale. The daily releases are disaggregated from the monthly releases of the reservoir into the river using the ratios of daily inflows to monthly inflows into the reservoir, with a view to maintain a similar flow regime between inflows and releases.

2.3 Methods of Estimating Hydrologic Alteration (HA)

Range of Variability Approach Herein, the statistics of natural flow series are estimated using the daily inflow data into the reservoir. The lower and the upper thresholds of the target range of RVA for each of the IHA are their respective 33rd and 67th percentile values. The hydrologic alterations of individual indicators are calculated as.

$$D_{RVA,m} = \left|\frac{N_{o,m} - N_{e,m}}{N_{e,m}}\right| \times 100\% \tag{16}$$

in which $N_{o,m}$ and $N_{e,m}$ are respectively the number of post-impact (regulated) and pre-impact (unregulated) years in which the value of the m^{th} hydrologic indicator lies within the target range.

Histogram Comparison Approach The HCA is based on the comparison of the pre-alteration and the post-alteration histograms of each IHA. The data range of the inflow statistics of each indicator is divided into a number of classes and both class-by-class and cross-class correspondence are used to estimate its similarity degree (S_m), that reflects how many features of the histogram of the unregulated flows (inflows) remain in that of the regulated flows (reservoir releases). Following this, the alteration degree ($D_{HCA,m}$) of the m^{th} indicator is computed as the complement of the similarity degree (Huang et al. 2017).

$$i.e.,\ D_{HCA,m} = (1 - S_m) \times 100\% \tag{17}$$

where $D_{HCA,m}$ ranges from [0,100%].

The overall hydrologic alteration (HA) for RVA as well as HCA are then estimated using the overall mean approach (Shiau and Wu 2007) given by Eq. 18a and 18b as:

$$HA - RVA = \left(\frac{1}{G}\sum_{m=1}^{G} D_{RVA,m}^2\right)^{1/2} \tag{18a}$$

$$HA - HCA = \left(\frac{1}{G}\sum_{m=1}^{G} D_{HCA,m}^2\right)^{1/2} \tag{18b}$$

in which $m=1,2,\ldots,G$ denotes the number of respective PCA-selected indicators and $D_{RVA,m}\ and\ D_{HCA,m}$ refer to the individual alterations estimated using RVA and HCA respectively, in separate simulation modules.

2.4 Parameterization-Simulation-Optimization (P-S-O) Framework

The developed reservoir parameterization-simulation model is linked with the source code of Borg-MOEA search algorithm, which is obtained from its developers (Hadka and Reed 2013) on personal request. The objective functions and the constraints are configured for the P-S-O run. The parameters of the Borg MOEA are set to the default values as recommended by the developers. A work flow diagram is presented in Fig. 2 which shows the linkages of the parameterization of the decision vector, the reservoir simulation module, the HA estimation module and the optimization model. The optimization model evaluates the two objective function values and checks the E-flow constraint for feasibility. The random population initially generated goes through successive genetic operations in Borg-MOEA over several thousand generations (leading to about 10–20 million evaluations) before reaching convergence.

3 Case Example

The long-term monthly operation of the Bhadra reservoir across the Bhadra River in southern India (Fig. S-1.1 of supplement-1) is the case example chosen to illustrate the efficacy of the HA estimation approach HCA over the popular RVA in obtaining rational and accurate estimates of HA and its influence on arriving at realistic optimal monthly E-flow targets and

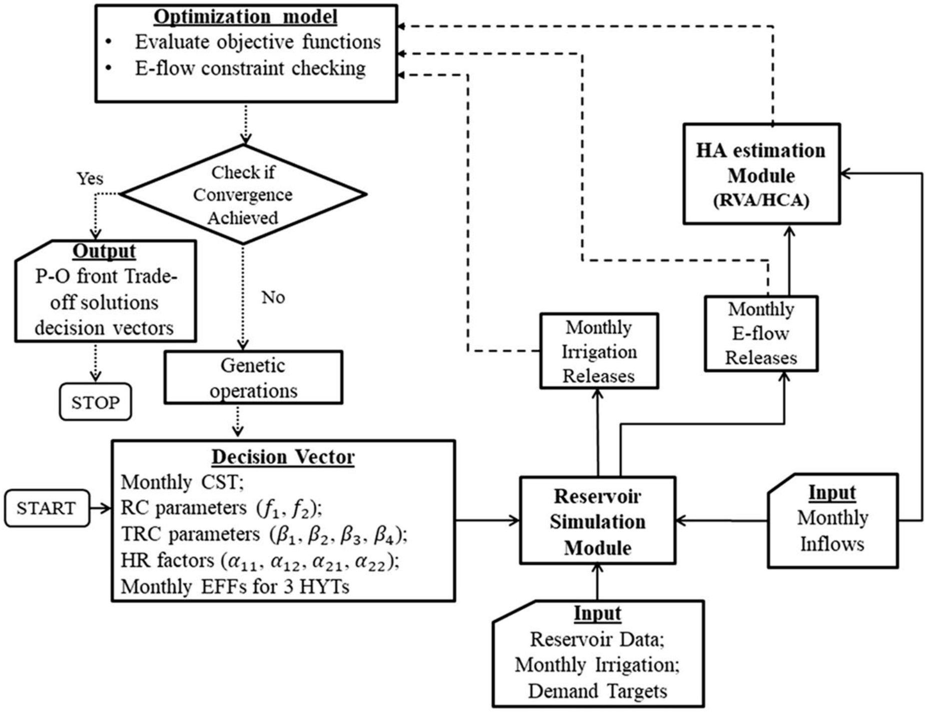

Fig. 2 Work flow Diagram of the proposed P-S-O framework

reliable trade-off between Irrigation MSI and HA at the reservoir level, employing the proposed P-S-O framework. Bhadra reservoir is primarily an Irrigation project built to increase the agricultural production in the semiarid tracts of four districts in the state of Karnataka. The data regarding daily inflows to the Bhadra reservoir for 38 years (1977–2015), monthly Irrigation demands and monthly evaporation are collected from the Bhadra reservoir project report (Karnataka Neeravari Nigam Limited 2007). The gross and the live storage capacities of the reservoir are 2025 and 1784 Mm^3, respectively. The average annual rainfall of the basin is 2752 mm and 90% of the rainfall occurs during the southwest monsoon season (June to September). The Kharif (June to November) season happens to be wet and the Rabi (January to May) season is dry and most of the crop water requirement in Rabi season is met by Irrigation water conveyed through the canals taking off directly from the reservoir. Thus, the E-flows released into the river downstream and the Irrigation releases are mutually exclusive. Although the Irrigation water demand is quite high during both seasons, a large amount of water is to be stored in the reservoir during Kharif season, to meet the Rabi season demands. This poses a challenge to maintain the natural high flows and flood pulses during the wet season, which was also pointed out in the prior studies done by Babu and Kumara (2009) and Kumara et al. (2010). The Rabi season Irrigation demands proposed in the project report are too ambitious, and hence the same are reduced by 20% in this research work. The monthly Irrigation demands adopted in this study and the mean monthly flows into the reservoir are presented in Table S-1.1 of supplement-1.

Since drinking water supply and hydropower demands are not significant in this project, they are not considered in the current study, although the P-S-O framework developed can handle these purposes as well. The discussion with the Bhadra reservoir authorities has revealed the absence of a well-defined operation policy for providing the E-flow requirements. Also, extensive database on hydrology-ecology relationships and hydraulic-habitat requirements for various key species in this river are yet to be developed, as in case of most other Indian rivers (Jain and Kumar 2014). The consideration of inter-annual variation is crucial in monsoon-based river-reservoir systems. Accordingly, the optimal monthly E-flow targets at the reservoir are derived in terms of MMF corresponding to the three HYTs (dry, normal and wet), classified based on the thresholds of 25th percentile and 75th percentile flows obtained from the available annual inflow data. For the seven months (June-December), the E-flow targets are considered as decision variables (expressed as a fraction of the respective MMF), while the same for the remaining five low flow months are fixed as MMF itself (Table S-1.1).

4 Results and Discussion

4.1 Deriving Optimal E-flow Targets Using HCA

4.1.1 Selection of Subset of IHA and Fixing Range of E-flow Fractions

Principal Component Analysis (PCA) is employed to select the subset of Indicators of Hydrologic Alteration (IHA) with the intent of reducing the effect of inter-correlation (Gao et al. 2009) among its statistics. The top 5 Principal Components (PCs) that explain 94% of the variance comply with the Kaiser-Guttman criterion (Guttman 1954). The indicators with the highest loading in terms of absolute values from each of these 5 PCs that are selected to form the subset of IHA are: annual maxima of 7-day means, monthly median flow of December, base flow index, annual minima of 30-day means and monthly median flow of January (Table S-1.2 of supplement-1). Based on several trial runs using the P-S-O framework, the lower and the upper thresholds for the monthly E-flow targets for the seven months (June-December) have been fixed respectively as 0.3 and 0.85 times the respective MMF. The details of the same are not shown here for brevity. The E-flow targets for the low flow months (January to May) are prefixed as equal to the respective MMF for all HYT.

4.1.2 Effect of Limiting the Maximum Average Monthly E-flow Deficit

The objective function "$Minimize\,HA$" employed as a surrogate for maintaining or restoring the health of the river ecosystem, may yield high optimal E-flow targets in certain months, which may not be realistic for implementation at the reservoir, since the plausible E-flow releases from the actual operation may happen to be way too short of the target derived. To overcome this anomaly, a limiting constraint on the maximum average monthly E-flow deficit is introduced in the present research work. Herein, the multi-objective simulation-optimization model run with the objectives "$Minimize\,MSI_{IR}$" and "$Minimize\,HA$" and without the limiting constraint on E-flow deficit is denoted as IMHA1-HCA, while the run with the same objectives but with the limiting constraint on

E-flow deficit (≤20%) is denoted as IMHA-HCA. The P-O fronts of the IMHA1-HCA and IMHA-HCA are presented in Fig. 3, wherein it may be observed that the range of HA-HCA values encompassed in the solution space of IMHA1-HCA is very small and quite low (between 21.3% and 24%). The optimal E-flow targets corresponding to such low HA-HCA values are too challenging to be met for a regulated reservoir with high pre-fixed irrigation demand targets. While, the range of the solution space of HA-HCA in case of IMHA-HCA is much wider and seemingly reasonable (between 27.89% and 40.95%). This is confirmed through the following post-optimal analysis.

The optimal monthly E-flow target demands of two P-O solutions having HA-HCA≤33.33% (shown by yellow triangles in Fig. 3) selected from the P-O front of IMHA1-HCA and that of the two P-O solutions (shown by yellow circles in Fig. 3) picked from the P-O front of IMHA-HCA are presented in Table 1. The optimal E-flow targets derived in case of IMHA1-HCA are much higher in four to five months in the normal flow years than that of IMHA-HCA, the highest being in one of the high flow months, August. Post-optimal analysis shows that such unrealistically high optimal E-flow targets yield high average monthly E-flow deficits (15–82%) in 6 consecutive months, February to July, which is unacceptable from the implementation point of view for the long-term reservoir operation. While, the optimal E-flow targets derived from IMHA-HCA seem to be reasonable and yield much less E-flow deficits (average monthly E-flow deficits range between 0.6% and 20% with a range of 13–20% in 5 consecutive months, March to July). The above analysis establishes the need for the introduction of the E-flow constraint, which was not included in similar earlier research works dealing with E-flow optimization.

The detailed discussion on the variation of optimal E-flow targets and the corresponding Irrigation deficits along the P-O front of IMHA-HCA, is presented in supplement-2, considering six P-O solutions. Following this, the efficacy of the proposed P-S-O framework in obtaining a reasonable trade-off between Irrigation MSI and HA-HCA, while meeting the pre-specified monthly Irrigation targets and the derived monthly E-flow targets enabled

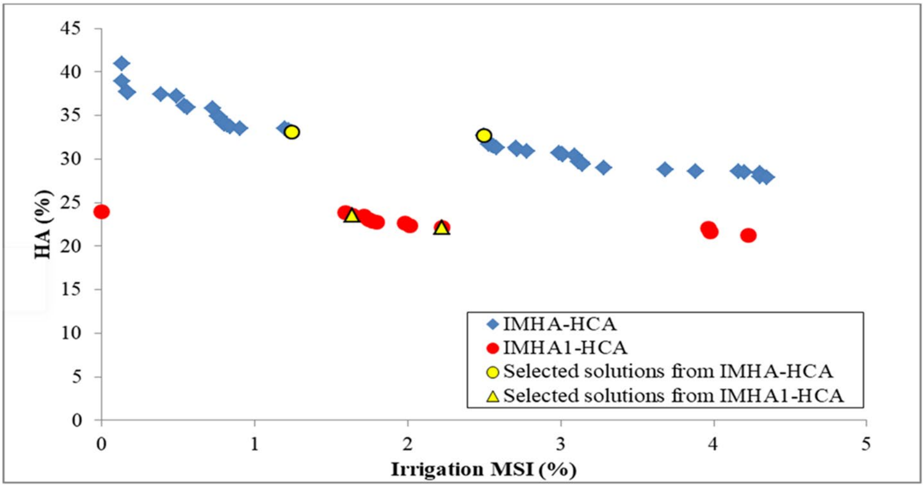

Fig. 3 Comparison of the Pareto-fronts obtained from the multi-objective optimization runs with and without the limiting constraint on the maximum average monthly E-flow deficit

Table 1 Optimal monthly E-flow targets for the four selected solutions two each from the P-O fronts of IMHA1-HCA and IMHA-HCA

Run	Irr MSI (%)	HA-HCA (%)	Year type	Optimal monthly E-flow targets ($\times 10^6 m^3$)											
				J	J	A	S	O	N	D	J	F	M	A	M
IMHA1-HCA	1.64	23.54	D	73	268	246	97	63	30	14	27	15	10	11	18
			N	104	413	630	104	137	30	22	27	15	10	11	18
			W	73	377	365	275	74	31	19	27	15	10	11	18
	2.22	22.15	D	89	231	330	97	63	30	14	27	15	10	11	18
			N	101	421	628	98	132	30	25	27	15	10	11	18
			W	73	378	298	264	75	31	15	27	15	10	11	18
IMHA-HCA	1.24	33.12	D	85	246	251	132	63	30	14	27	15	10	11	18
			N	73	231	246	97	63	30	25	27	15	10	11	18
			W	118	234	634	97	63	30	14	27	15	10	11	18
	2.5	32.67	D	73	231	452	97	63	30	14	27	15	10	11	18
			N	73	235	246	101	67	30	25	27	15	10	11	18
			W	73	648	268	108	77	40	21	27	15	10	11	18

through a synchronous operation of storage rule curves, transition rule curves and fuzzified hedging parameters, is discussed in supplement-2.

4.2 Deriving Optimal E-flow Targets Using RVA

The indicators with the highest loading in terms of absolute values from the top 6 PCs that comply with the Kaiser-Guttman criterion are selected to form the subset of IHA for computing HA-RVA. The six indicators are: monthly median flow of May, rise rate, annual maxima of 7-day means, monthly median flow of July, annual maxima of 90-day means and low pulse count (Table S-1.3 of supplement-1). The multi-objective model with objectives "$Minimize\ MSI_{IR}$" and "$Minimize\ HA - RVA$" and constraints given by eqs. (2) to (6), denoted as IMHA-RVA, differs from the model variant IMHA-HCA (already discussed) only in the method of estimation of HA. The Pareto-optimal front of IMHA-RVA model resulting from the P-S-O framework is shown in Fig. S-3.1 (supplement-3), wherein it is noted that the P-O front covers a wider range of solutions with Irrigation MSI (0.16–17%) and HA-RVA (52–5.83%), than that of IMHA-HCA. Based on the criterion of low-alteration category of HA (≤33.33%) and the implementability of the E-flow targets at the reservoir level from the deficit performance consideration (similar to the model run IMHA-HCA), only four P-O solutions (33.12–30.02%) (identified by yellow circles in Fig. S-3.1), are selected for further analysis and investigation. The detailed discussion on the variation of optimal E-flow targets and the corresponding Irrigation deficits along the P-O front of IMHA-RVA, is presented in supplement-3, considering the four P-O solutions.

4.3 Comparison of RVA and HCA in the Estimation of HA

Since direct one-to-one comparison of the results obtained from IMHA-HCA and IMHA-RVA models may not be appropriate due to the two different approaches of estimating HA, a notional comparison of the post-optimal individual alterations is presented. For this, the following three solutions from the respective P-O fronts of IMHA-HCA and IMHA-RVA with nearly the same Irrigation MSI are considered:

IMHA-RVA (Irrigation MSI, HA-RVA): (2.46, 30.58); (2.84, 30.44); (3.2, 30.16)
IMHA-HCA (Irrigation MSI, HA-HCA): (2.50, 32.67); (2.78, 30.92); (3.28, 28.95)

The assessment of the individual alterations of the chosen subset of indicators estimated using RVA and HCA considering all the respective class intervals corresponding to the entire range of inflows, are shown in Fig. 4, for the P-O solutions IMHA-RVA-30.58 and IMHA-HCA-32.67. It may be observed from Fig. 4 (b), (c), (e) and (f) that for four (low pulse count, monthly median of May, monthly median of July and rise rate) out of six indicators, the values of individual alterations $(D_{RVA,m})$ are found to be quite low (between 0 and 14.29%).

Especially, in case of low pulse count, the frequencies corresponding to releases as well as inflows within the RVA boundaries (9.87 and 16.13) are identical, resulting in zero alteration. This assessment is false, since these boundaries cover only two classes (classes 2 and 3) (Fig. 4b), while the low pulse count assessed from the inflow series falls outside these boundaries in a number of years. Similar observation and explanation hold good for the

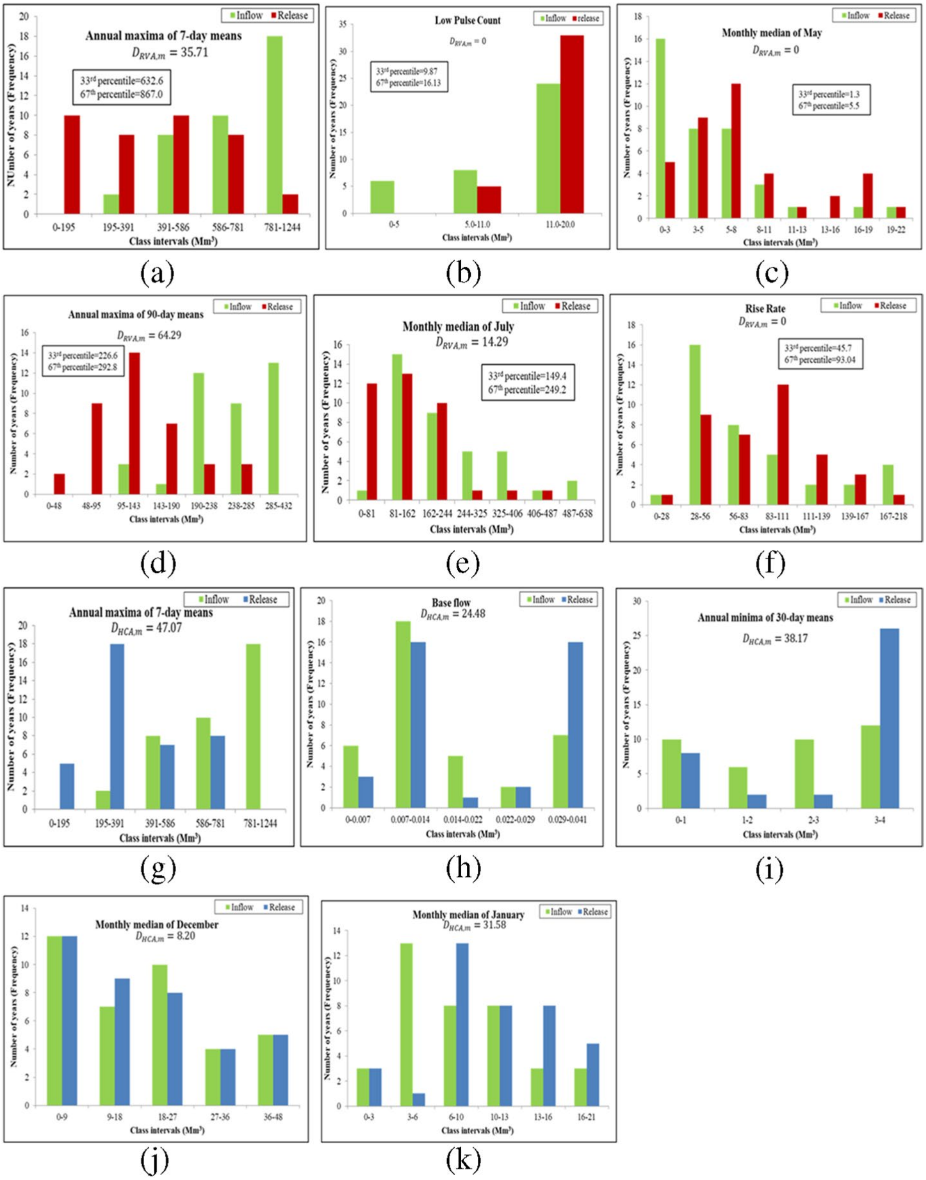

Fig. 4 Assessment of hydrologic alterations of (**a**) annual maxima of 7-day means; (**b**) low pulse count; (**c**) monthly median flow of May; (**d**) annual maxima of 90-day means; (**e**) monthly median flow of July; (**f**) rise rate corresponding to IMHA-RVA-30.58 and (**g**) annual maxima of 7-day means; (**h**) base flow; (**i**) annual minima of 30-day means; (**j**) monthly median flow of December and (**k**) monthly median flow of January corresponding to IMHA-HCA-32.67 across the various class intervals covering the entire range of inflow statistics

alteration of the other three hydrologic indicators too, which is evident from Fig. 4(c), (e) and (f), respectively.

For the other two indicators, annual maxima of 7-day means and 90-day means, the values of individual alterations are quite high. This is because the unregulated flows have high frequency of occurrence of these two indicators at class intervals of high flows and low frequency at class intervals of low flows, whereas it is vice versa in case of regulated flows from the reservoir. In essence, the limited target range (33rd percentile to 67th percentile) considered and the non-inclusion of variability within this range and not accounting for both frequency and variability in the range, outside the target range have resulted in inaccurate and unrealistic estimate of HA using RVA.

On the other hand, the individual alterations of the chosen subset of indicators estimated employing HCA seem more reasonable and realistic, which can be observed from the histograms plotted in Fig. 4 (g) – (k) for the indicator values assessed from the inflow series as well as the releases series, for Irrigation MSI 2.50%. It is more obvious in case of monthly median flow of December with minimum variability between the inflow and the release statistics resulting in lowest alteration (8.20%).

For the case of annual maxima of 7-day means, the scanty high flow pulses in release from the reservoir are expected to lead to its high alteration, but this is underestimated in case of IMHA-RVA, by way of neglecting the differences in the class intervals other than the target range. The effect of regulating flows through the reservoir is very much sensed from the significant difference in the annual minima of 30-day means and the annual maxima of 7-day means across the various class intervals (Fig. 4 (i) (g)), leading to considerable violations, on account of flow regulation, and the same are reflected in the alterations of these two indicators (38.17% and 47.07%).

It may be noted that the alteration in the annual maxima of 7-day means (the common PCA-selected indicator between HCA and RVA) points to a lower value (35.71%) for the RVA variant, which is an underestimate. If the entire range of inflow class intervals are considered (as in HCA) the alteration would have been 50.63%, which is more than that of IMHA-HCA-32.67 (47.07%). The same trend in individual alterations can be observed from the hydrologic alterations of IMHA-RVA-30.44 (Fig. S-4.1), IMHA-HCA-30.92 (Fig. S-4.2), IMHA-RVA-30.16 (Fig. S-4.3) and IMHA-HCA-28.95 (Fig. S-4.4) as well, that are shown in supplement-4.

In fact, the individual alterations of several of the P-O solutions obtained from IMHA-HCA (Table S-4.1 of supplement-4) reinforce that the HA estimates from IMHA-HCA are accurate and stable. On the contrary, the individual alterations of several of the P-O solutions of IMHA-RVA are underestimated (Table S-4.2 of supplement-4), due to the reasons already discussed, emphasizing that the HA estimates from IMHA-RVA are unrealistic and hence are not reliable.

Overall, it can be concluded that the proposed model IMHA-HCA yields a realistic and accurate estimate of hydrologic alteration by way of considering the frequency and the variability of the indicators within each class interval and across the classes, encompassing the entire range of inflow statistics. Hence, the PCA-selected subset of IHA and the optimal E-flow targets derived from IMHA-HCA seem to be acceptable and realistic for implementation at the reservoir level. Moreover, the trade-off between MSI of Irrigation and HA-HCA obtained from IMHA-HCA is reasonable and reliable. While, those obtained from IMHA-RVA model, may not be dependable for implementation.

5 Summary and Conclusions

In the multi-objective E-flow optimization formulation proposed in the current research work for long-term planning of reservoir operation, HCA is adopted for the estimation of HA and the resulting performance is compared with that of RVA in terms of the trade-off solutions obtained, optimal monthly E-flow targets, and the individual alterations achieved in the river through a post-optimal analysis. This is one of the main contributions of the current research work. Another contribution is the inclusion of a limiting constraint on the maximum average monthly E-flow deficits in the proposed E-flow optimization formulation in order to ensure the implementability of the derived optimal E-flow targets at the reservoir level. The parameterization of the reservoir operation rules involves rule curves concerning carryover storage, Irrigation, E-flows and their transitions and fuzzified hedging factors as the decision variables with monthly water availability being used as the hedging trigger, which is another novelty. The E-flow targets are derived as fractions of the respective mean monthly flows for the three hydrologic year types (dry, normal and wet), accounting for the intra- and the inter-annual flow variability. The robust meta-heuristic Borg-MOEA is employed as the search engine in the framework. The highly regulated Bhadra reservoir in Southern India is chosen as the application case example. This research study is the first of its kind done in connection with E-flow optimization in any of the south Indian monsoon-based river systems.

The Pareto-optimal range of Irrigation MSI and HA obtained by using HCA for HA estimation, is found to be more reasonable and realistic than that obtained using RVA for the regulated river-reservoir system considered. The constraint introduced to limit the maximum average monthly E-flow deficits enables deriving realistic E-flow targets at the reservoir. A notional comparison of the two approaches of HA estimation, RVA and HCA, reveals that the individual alterations of the various indicators appear to be reasonable for all the solutions along the P-O front of IMHA-HCA, thus establishing the reliability of the HCA in estimating HA and consequently the optimal E-flow targets derived and the reservoir operating policy. While, the RVA underestimates the individual alterations due to which the HA estimate, the optimal E-flow targets derived and the reservoir operating policy may not be reliable.

The findings from the current study need to be verified by applying to other hydrologic regions with different intra- and inter-year variabilities of rainfall and streamflow. This will require modifying the thresholds of the E-flow targets; considering the classification of hydrologic year types depending on the hydro-climatic zone and the hydrologic regime; and specifying the limiting percentage of the E-flow deficit constraint depending on the competing demands of the beneficial uses and the storage capacity of the reservoir. The selection of subset of IHA is to be done using PCA on the individual alterations estimated based on the observed flow data of the study region of concern.

Although HCA is reported to have addressed the major shortcomings of RVA, it has a few limitations of its own. Hence a more reliable, recently proposed joint probability density difference approach (Zhong et al. 2024) for HA estimation can be used in the P-S-O framework and consequent improvement (if any) concerning the optimal E-flow targets and the trade-off decisions can be investigated. Future research should also address extending the proposed framework to basin level, considering multiple reservoirs and river reaches, adopting holistic EFA techniques. This would require rigorous data collection and inputs from ecological experts and also hydraulic routing and water quality modelling along the entire river stretch. Moreover, the effectiveness of the proposed hedging strategy can be tested with monthly flow forecasts obtained from a good forecast model.

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Author Contributions The study was conceptualized by both the authors. Ruby Jose Janakiraman developed the relevant codes (computer programs), performed the result analysis and prepared the original draft. Srinivasan Kasthurirengan contributed in supervising and writing-review and editing the manuscript.

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Data Availability The source codes for estimating the IHA indicators, the code for reservoir simulation, and the code for PCA, the supplementary data and the results obtained from the proposed P-S-O framework are available online through the link https://github.com/RubyJose/FRC-HCA-RVA.git. The source code of the search engine, Borg MOEA, used in this research work is obtained from its developers on personal request, and hence cannot be shared.

Declarations

Ethics Approval This paper has neither been published nor been under review for publication elsewhere.

Consent to Participate The authors have participated in the preparation of this paper for publication in the Water Resources Management.

Consent to Publish The authors declare their consent to publication of the manuscript in "Water Resources Management" journal.

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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