Chapter 11
Advancing Joint Design and Operation of Water Resources Systems Under Uncertainty

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11.1 Introduction

Hydropower has been employed as the first renewable energy source for electricity generation back in the 19th century and today it still plays a major, multidimensional role in the electricity sector worldwide for a variety of reasons. Firstly, it is a clean and renewable source of energy that generates local, affordable power fostering sustainable development, as promoted under the Sustainable Development Goals (SDGs) [1]. Secondly, it allows to reduce dependence upon imported fuels, associated to high risks of price volatility and supply uncertainty. Then, hydropower dams can offer multiple co-benefits, from storing water for drinking and irrigation, to being used for drought-preparedness, flood mitigation and recreation. In the end, hydropower is very competitive with other electricity sources from a costs point of view and provides a rapid-response when intermittent energy sources (e.g., solar) are off-line [2, 3].

Hydropower is currently responsible for about 16% of global electricity production, a percentage that is projected to substantially increase due to the doubling of the total installed hydropower capacity expected by 2050 [4]. Since developed countries already exploited more than 50% of their hydropower potential, most of the future hydropower expansion is predicted to occur in developing countries, which still present a vast untapped potential. Among others, Africa represents an extreme case with its almost 90% of undeveloped hydropower potential, with respect to a 25% global exploitation rate on average [2, 5]. This has motivated potential investments in the construction of approximately 3,700 new dams in the near future [6], a large share of which will be built in Africa, Asia and Latin America [4], leading to potential benefits in terms of increased energy supply but also negative impacts on the environment (e.g., losses of fish biodiversity, deforestation).

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In the future, changes in water availability and extreme events (e.g., droughts) due to climate change coupled with high rates of population growth will contribute to an increase in both migration rates within a single region, as well as energy and food demands, putting additional pressures on already stressed water resources. Globally, both existing and planned dams will thus have to face a vast array of future challenges, such as water scarcity, and growing resource conflicts in their demands (e.g., hydropower production vs irrigation water supply).

When planning new dams, integrated, strategic approaches must be therefore employed to find a balance between key economical, social and environmental objectives, while accounting for different water users and changes in external conditions that might strongly impact water resources systems in the future.

11.1.1 Research Challenges

The planning of large dams traditionally consists in basin-wide assessments of the potential economic outcomes of different designs via financial metrics (e.g., net present value) to evaluate their corresponding financial value [7, 8]. This approach combines costs and monetized downstream impacts of large water infrastructures into a single aggregate monetary value, disregarding potentially conflicting objectives and trade-offs among different water users within the basins of focus.

Secondly, over the last fifty years the interdependency between dam size and operations has been largely neglected by traditional engineering approaches relying on the widespread Rippl method [9], aimed at identifying a single optimal dam size based on a sequence of pre-defined releases and observed inflows [10, 11].

Third, the long design life of large dams critically exposes them to future uncertainties related to climatic and socio-economic changes. Yet, their planning is usually performed assuming stationarity in the long-term natural processes and without accounting for uncertainty in the external drivers. Since the assumption of a stationary climate is unlikely to be valid in the future [12], uncertainties in the main external drivers must be taken into account during dam planning in order to design robust infrastructures that are able to perform satisfactorily in the future with respect to multiple sources of uncertainty.

Building on the above mentioned research challenges, this contribution proposes a set of modelling and optimization tools converging in multiple, novel integrated frameworks for thoroughly capturing interdependencies between planning and operation in non-linear systems, also with respect to uncertainty in the main external drivers (e.g., hydro-climatology, human demands). The main focus is on water resources systems and specifically on coupling dam sizing and operation design. In particular, Sect. 11.2 presents a novel Reinforcement Learning (RL)-based approach to integrate dam sizing and operation design, while significantly containing computational costs with respect to alternative state-of-the-art methods. On the other hand, Sect. 11.3 shows a novel framework combining Multi-Objective Robust Decision Making and Evolutionary Multi-Objective Direct Policy Search into a novel approach to dam sizing, which internalizes the operation design problem and explicitly considers uncertainty in external drivers.

11.2 Reinforcement Learning for Designing Water Reservoirs

The method proposed relies on a novel algorithm, called Planning Fitted Q-Iteration (pFQI), which extends the batch-mode RL Fitted Q-Iteration (FQI) algorithm developed by [13] by enlarging the original FQI state space to include the discrete planning decision (i.e., dam size) as an additional state variable. The key idea behind pFQI originates from the Multi-Objective Fitted-Q Iteration (MOFQI) algorithm developed by [14]: the continuous approximation of the action-value function originally performed by FQI over the state-action space is now enlarged to the planning space by including dam sizes as new variables within the arguments of the action-value function. This enables pFQI to approximate the optimal operating policy associated to any dam size within a single learning process.

This new algorithm therefore overcomes the limitations and biases introduced by traditional sizing methods by directly addressing the strict interdependency between dam size and operation within an integrated framework through an operating policy parametric in the dam size. Secondly, it overcomes the high computational costs associated with state-of-the-art nested and integrated approaches by solving a single operation optimization via pFQI, as the resulting policy can be used to simulate the optimal operations of all the possible dam sizes associated to alternative trade-offs between least cost planning and operating objectives (e.g., downstream water supply). This characteristic contributes to significantly reducing the computational burden of pFQI.

The pFQI algorithm is tested on the multi-objective numerical case study, consisting of a synthetic water reservoir that must be sized and simultaneously operated to satisfy the water demand of downstream users.

11.2.1 pFQI Algorithm

The novel principle underlying the pFQI algorithm is to enlarge the traditional FQI state-action (x_t, u_t) space to include an additional time invariant state variable, namely the dam size $\theta \in \Theta$. This latter is described by the dummy deterministic state transition function $\theta_{t+1} = \theta_t = \theta$, where the dam size does not evolve in time, assuming a constant value throughout the entire evaluation horizon. The key idea behind pFQI originates from the Multi-Objective Fitted Q-Iteration (MOFQI) algorithm developed by [14], where linear combinations of preferences (weights) assigned to the objectives represent the dummy state variable to generate an entire Pareto front in a single optimization run. The resulting enlarged state-action space of pFQI can be therefore defined as $(\tilde{x}_t, u_t)$, where $\tilde{x}_t = [x_t, \theta]$, over which the optimal Q-function is continuously approximated. A new learning dataset $\mathcal{F}_\theta$ is thus produced, enlarging the original set of experience samples $\mathcal{F}$ as follows:

$$\mathcal{F}_\theta = \left\{ < \tilde{x}_t^i, u_t^i, \tilde{x}_{t+1}^i, g_{t+1}^i >, \quad i = 1, \ldots, N_\theta \right\} \tag{11.1}$$

where $N_\theta = N \cdot n_\theta$ is the number of tuples in the new pFQI dataset and n_θ is the number of sampled dam sizes θ. Since n_θ new tuples are produced for each four-tuple in $\mathcal{F}$, N_θ is larger than N. A tabular version of the Planning FQI algorithm proposed in this study is presented in Algorithm 1.

Likewise the traditional FQI algorithm, pFQI exploits the information in the sample dataset $\mathcal{F}_\theta$ to iteratively approximate the optimal action-value function $Q^*(\tilde{x}_t, u_t)$ over the enlarged state-action space $(\tilde{x}_t, u_t)$. Being the optimal operating rule, and thus operating policy, strictly related to the Q-function, the pFQI algorithm is also able to learn a continuous approximation of the optimal operating policy $\pi^*(\cdot)$ over the enlarged state space $\tilde{x}_t = [x_t, \theta]$. This policy therefore results parametric in the dam size $\theta \in \Theta$, and can be used to operate any dam size within this feasibility set.

Algorithm 1 Planning FQI Algorithm

Inputs: a learning set of tuples $\mathcal{F}_\theta$ and a regression algorithm
Initialization:
Set $h = 0$
Set $\hat{Q}_0(\cdot) = 0$ over the whole enlarged state-action space $\tilde{\mathcal{X}} \times \mathcal{U}$
Iterations: repeat until stopping conditions are met
- $h \leftarrow h + 1$
- build the training set
$TS_\theta = \left\{\left(IN^i, OUT^i\right), i = 1, \ldots, N_\theta\right\}$
where
$IN^i = \left(\tilde{x}_t^i, u_t^i\right)$
$OUT^i = g_{t+1}^i + \gamma \min_{u_{t+1}} \hat{Q}_{h-1}\left(\tilde{x}_{t+1}^i, u_{t+1}^i\right)$
- Run the regression algorithm on TS_θ to get $\hat{Q}_h(\tilde{x}_t, u_t)$
Output: derive the final operating policy $\hat{\pi}_h^*$ parametric in θ

11.2.2 Comparison with Traditional Least Cost Dam Design

In order to prove the importance of capturing interdependencies between dam size and operations, we compare the least cost planning solutions identified via traditional sizing methods and the optimal system configurations designed via pFQI.

The traditional sizing method identifies the least cost dam size under a pre-defined operating policy $\bar{\pi}$ while meeting a specific reliability rate. The pre-defined operating policy $\bar{\pi}$ adopted is the Standard Operating Policy (SOP), which assumes that the system operator is able to fully supply the downstream demand, unless constrained by water availability in the reservoir storage and current period inflow [15]. We test four different reliability rates $\bar{r}$, namely 95% (acceptable value for a dam aimed at supplying water for agriculture according to [16] and [17]), 90%, 85% and 80%, which are associated to four alternative least cost dam sizes operated under the same given operating policy $\bar{\pi}$. This latter consists of a target release equal to the downstream water demand w to be discharged at each time step.

Figure 11.1 shows the performance of four alternative least cost dam sizes optimized under four different reliability rates $\bar{r}$ (pink circles), along with the performance of two specific dam sizes θ_{opt} and θ_{sim} attained via nested approach (yellow triangles) The four least cost dam sizes increase proportionally with the associated reliability. For each of them, the operating objective (i.e., water supply deficit) is computed assuming a constant release equaling the downstream water demand unless constrained by the physical water availability, namely the pre-defined Stan-

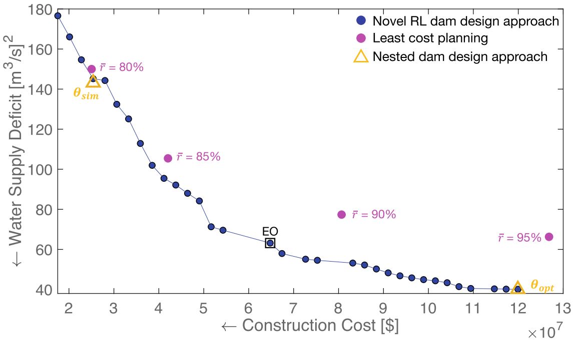

Fig. 11.1 2D-objective space where both the least cost planning solutions (pink circles) and the two nested solutions (yellow triangles) are compared against the system configurations identified via novel RL approach relying on the pFQI algorithm (blue circles). Arrows indicate the direction of preference in the objectives

dard Operating Policy $\bar{\pi}$. The four least cost system configurations are compared against the optimal dam sizes and associated operating policy identified via novel RL approach (blue circles). In this first experiment, the size of the learning dataset $\mathcal{F}_\theta$ of the pFQI algorithm employed during the novel RL operation optimization is $n_\theta = 11$. As can be observed, the RL solutions dominate the four least cost system configurations in terms of system performance. In particular, the dam size associated to the highest reliability rate $\bar{r}$ = 95%, which has a cost equal to $ 127 million (106 Mm^3), is weakly dominated by the Equivalently Operated (EO) solution identified via novel RL approach (J^c = $ 65 million and size equal to 54 Mm^3).

A 50% smaller (thus less costly) infrastructure could be built while achieving the same water supply deficit, meaning that the pFQI algorithm is able to fully capture the interdependency between dam size and operation within an integrated framework, yielding system configurations that strongly outperform the performance achieved under traditional sizing methods. This is particularly true for reliability rates that are equal to or higher than 85%, where the advantages of jointly optimizing dam size and operation can be seen in terms of a significant deviation between the least cost planning and the RL solutions. For lower reliability rates, the corresponding water supply deficit is so high that almost any operating policy is able to attain it. The potential benefits of optimizing the operation thus become almost negligible and the least cost system configuration associated to an 80% reliability approaches the RL solutions. By coupling smaller dam sizes to more efficient operating schemes, and accounting for the impacts of short-term operating policies on the long-term system design, the novel RL dam design approach is therefore able to identify less costly, more efficient system designs.

11.3 A Novel Robust Assessment Framework

In this section, we propose a robust dam design framework that is: (i) multi-objective; (ii) capable of joint planning and management, capturing the interdependencies between dam size and the associated trade-offs across candidate operating policies; (iii) integrating state-of-the-art stochastic optimization, yielding design system configurations that are less vulnerable to intrinsic, stationary hydro-climatic variability; and (iv) directly accounting for robustness to long term deep uncertainties, clarifying how alternative system configurations perform with respect to uncertain drivers (e.g., inflows and demands).

We carefully evaluate the potential of this framework through an ex-post analysis of the Kariba dam in the Zambezi river basin, which provides a rich and challenging opportunity to demonstrate the limitations of prior standard sizing approaches.

11.3.1 Methodological Approach

Our proposed integrated design and operation framework therefore captures (i) key trade-offs between water users, (ii) how dependencies in dam sizing and operations influence these trade-offs, (iii) how intrinsic, stationary hydro-climatic variability affects dam design, and (iv) the ultimate robustness of the water infrastructures designed. Drawing on the methodological taxonomy for robustness frameworks suggested by [18], we present in the following the four main elements of our proposed framework.

The first element is the generation of decision alternatives, namely alternative dam sizes with associated candidate operating policies, via multi-objective optimization under both historical and well-characterized, stationary streamflow uncertainty. It is a useful insight to discover how planning and management trade-offs evolve when moving from historical observation record to a better statistical representation of the internal variability of extremes. Put more simply, the available historical observation record by itself is a poor estimator of rare extremes that are potentially highly consequential to dam sizing and operations.

The second element is strongly linked to the search in the first element by how alternative states of the world (SOWs) are sampled and exploited in the overall analysis. Sampling strategies can be classified into three different groups: (i) historical records, representing a single SOW composed of the available observed time-series; (ii) stationary synthetic records, where each SOW is obtained by sampling well-characterized, stationary model for uncertain hydro-climatic factors; and (iii) deeply uncertain scenarios, where each SOW is generated by globally sampling a suite of deeply uncertain drivers. As discussed above, stationary synthetic records better capture system's stochastic hydrology, where the historical autocorrelation of recorded streamflows is preserved while better accounting for their internal variability. As for sampling deep uncertainties, the broader suite of SOWs used to stress test systems are drawn from non-stationary future scenarios of both hydro-climatic (inflows) and socio-economic (irrigation demand) factors. The SOWs belonging to the first two groups are employed during the optimal alternatives generation phase, whereas the latter are used in the a-posteriori robustness assessment of the candidate alternatives identified.

Once the candidate alternatives for design and operation are re-evaluated over the deeply uncertain SOWs, their robustness is assessed in terms of global domain criterion satisficing metric [19, 20], namely the percentage of SOWs satisfying predefined performance requirements (third element). As an innovation in this study's assessment of robustness, instead of pre-specifying acceptable performance thresholds, we map the satisficing robustness measure into the objective space, forming a multidimensional satisficing surface.

The last element of our methodology is a sensitivity analysis conducted to identify which deeply uncertain factors are the most responsible for failing specific performance criteria (i.e., factor mapping or scenario discovery).

11.3.2 Assessing Robustness of Alternatives for Changing Demands and Hydrology

Figure 11.2 provides a broader evaluation of the hydropower maximizing (LH, MH, and SH) and compromise alternatives (LC, MC, and SC) for large L, medium M and small S dam sizes with respect to deeply uncertain changes in demands and hydroclimatology. These solutions were re-evaluated over our deeply uncertain scenarios, composed of 143 sampled combinations of changes in mean streamflow and irrigation demands. Here, the robustness of the different system configurations is assessed in terms of a satisficing surface, which maps the satisficing robustness measure across the conflicting objectives space for any combination of either hydropower (Fig. 11.2a) or multivariate (Fig. 11.2b) thresholds for both hydropower and irrigation deficit. In the case of the multivariate thresholds, the color of each point forming the satisficing surface is given by the exact value of the satisficing robustness measure, namely the percentage of SOWs satisfying that specific performance requirement on multiple objectives simultaneously.

Figure 11.2a distinguishes the hydropower focused robustness of the baseline forensic solution (i.e., historical operating policy associated to the existing Kariba dam size) relative to the large (LH), medium (MH), and small (SH) alternatives attained using the stochastic joint optimization. It is very clear that the existing Kariba

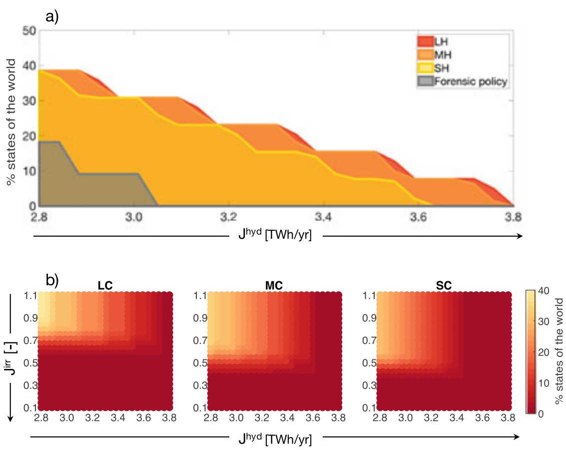

Fig. 11.2 Panel a: Cumulative distribution functions of the baseline forensic solution and the policy maximizing hydropower production H associated to three optimal dams sizes (S: Small, M: Medium, L: Large) across 143 deeply uncertain states of the world. Panel b: Mapping of the robustness in terms of satisficing metric of the compromise policy C in the 2D-management objective space. The color is given by the percentage of deeply uncertain states of the world that satisfy a specific multivariate threshold on both hydropower J^{hyd} and irrigation J^{irr} objectives (red = low percentage; green = high percentage). In both panels, arrows indicate the direction of preference in the objectives

design and operation does not in a general sense maximize hydropower. It has an extremely narrow hydropower production range (2.8–3.0 TWh/yr) where it meets performance goals for as few as 20% of sampled SOWs. Alternatively, Fig. 11.2a shows that the robustness of the large LH and medium MH dam sizes are similar to one another, as their cumulative distribution functions mostly overlap. This is due to the fact that the hydropower maximizing operating policies associated to these two dam alternatives behave the same, minimizing spillages and keeping releases constant regardless of the water level in the reservoir. Dam size starts playing an important role in robustness for small hydropower maximizing alternative (SH). Although this alternative spills large volumes of water due to its size limitations, it is striking that it fully outperforms the existing Kariba system being operated with the idealized bang-bang forensic solution, which aims at tracking a prescribed storage trajectory. Increasingly severe water scarcity captured in the deeply uncertain SOWs with respect to historical conditions causes the baseline forensic solution to fail as Kariba's operations are not able to drive the reservoir storage back to its prescribed storage trajectory. Note that the four cumulative distribution functions step-behavior is reflective of the discretized sampling of the deeply uncertain factor space across hydropower production levels (Fig. 11.2a).

The compromise alternatives (LC, MC, and SC) in Fig. 11.2b are evaluated for sustaining their performance in both the hydropower and irrigation deficit objectives for the more challenging deeply uncertain SOWs. It is clear in Fig. 11.2b that maintaining high levels of performance in both objectives is very difficult and, as a consequence, 0% of the sampled deeply uncertain SOWs meet the suite of performance goals for a large swath of mapped satisficing surface, regardless of dam size. However, there are some interesting differences across the dam sizes. Perhaps most surprisingly, the large compromise (LC) solution's robustness is not clearly superior to the medium size compromise (MC). The medium compromise (MC) alternative generalizes over lower irrigation deficits while still maintaining competitive performance in hydropower robustness (also noticeable in Fig. 11.2a). Clearly, volumetric size is not the sole control on the robustness of a design and the importance of operational policies are pronounced in the robustness results of Fig. 11.2b. Based on the solutions selected and discussed, medium (MC) and small (SC) compromise dam sizes are exploiting their operations to be more robust than the large (LC) compromise alternative. The small (SC) compromise dam is still disadvantaged volumetrically relative to the medium (MC) compromise alternative's reservoir capacity.

11.4 Conclusions

We presented two novel contributions whose main goal is to advance the current planning and operation of water reservoir systems, focusing on the coupling of dam sizing and operation design in order to thoroughly capture their interdependencies also with respect to uncertainty in the main external drivers.

Results show that capturing the interdependencies between dam size and operations has proved to be essential to effectively design smaller yet more efficient water reservoirs that strongly outperform the performance achieved under traditional engineering sizing methods, which instead neglect the optimal operation design phase. When employing our novel Reinforcement Learning (RL)-based approach on a numerical case study, where a synthetic reservoir must be sized and operated to meet downstream users water demand while minimizing construction costs, a 50% smaller (thus less costly) dam could be built without degrading the system performance achieved under the least cost infrastructure identified via traditional sizing method (i.e., Behavior Analysis). When instead we use our robust dam design framework to perform an ex-post analysis of the existing Kariba dam, which has been sized via traditional design methods assuming a pre-defined operating rule (i.e., target storage to be tracked), we are able to design a 32% less costly Kariba dam with respect to the existing one, without degrading system performance.

Secondly, a careful consideration of the broader array of future uncertainties within the planning phase is key for designing robust infrastructures, which will likely face a wide range of future challenges such as reduced water availability and rising frequency of extreme events (e.g., floods, droughts) related to climate change, together with increases in both energy and food demands due to population growth. By including stationary, hydro-climatic uncertainty within the Kariba dam design phase, we are able to identify well operated but reduced volume alternative reservoirs that can fully dominate larger designs in terms of their attained robustness. In particular, we clearly highlight that Kariba, even if optimally implementing its pre-defined operating rule, is critically vulnerable to stationary hydro-climatic variability, and that it produces less hydropower than a well sized run-of-the-river hydropower plant.

Future research should mainly focus on (i) including a broader array of external uncertainties in the coupled dam sizing and operation design problem in order to fully understand which uncertainties drive the robustness of water reservoir systems, by including them within the optimization process, and (ii) testing the contributed methodological approaches on complex transboundary, multi-reservoir systems, in order to explore potential interactions among several dams planned for the near future and that must be operated to satisfy different management objectives (e.g., environmental flow requirements).

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