Renewable and Sustainable Energy Reviews 132 (2020) 109910

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: http://www.elsevier.com/locate/rser

Efficient and robust hydropower system design under uncertainty - A demonstration in Nepal

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ARTICLE INFO

Keywords:
Decision making under deep uncertainty
Energy-food-water
Hydropower
Infrastructure investment
Multi-objective optimization

ABSTRACT

Interventions to increase benefits from energy-food-water-environment systems can involve changing infrastructure configurations and/or operational rules. In a context of complexity due to interdependencies and uncertainty, resource system intervention appraisal should consider multiple facets of system performance and a variety of plausible future conditions to achieve robust systems that balance multiple stakeholder definitions of acceptable performance. This paper proposes a novel multi-method decision-making under deep uncertainty approach to hydropower system design. The most efficient and robust designs are identified; those that maximize benefits and balance stakeholder interests despite uncertainty. It is applicable in any context where efficient and robust future hydropower systems are sought. The proposed approach is demonstrated in Nepal, showing the robustness benefits of diversified infrastructure systems; here the mixed development of both storage and run-of-river dams. Stress testing of a selected efficient and robust hydropower investment bundle reveals that institutional or financial uncertainties can most threaten the viability of assets, even when significant climate change is anticipated.

1. Introduction

Decision-making which impacts environmental resources often involves multiple stakeholders with conflicting perspectives, values and proposed solutions. Their ways of describing and bounding problems and their causes can influence the solutions they propose or prefer [1]. Such problems can be described as 'wicked' [2]. They are of increasing interest to researchers in water management [1,3,4], climate change [5,6] and environmental sustainability [7–11]. Wicked problems are often associated with decisions that are hard or uneconomical to reverse in practice, for example through construction of long-lived infrastructure. Their systemic repercussions may be difficult to predict [2].

Deep uncertainty can be a component of wicked problems, defined as a state where various parties to a decision do not know or cannot agree on the system and its boundaries, the outcomes of interest and their relative importance, and/or the prior probability distribution for uncertain inputs to the system [12]. Deep uncertainty is a concern in the field of infrastructure system design and climate change adaptation as traditional measures of expected utility are deemed inappropriate by some for managing risk in this context [13]. Decision making under deep uncertainty (DMDU) is an active area of research offering a variety of methods for wicked planning problems, including for example; robust decision making (RDM) [14], multi-objective robust decision making (MORDM) [15], multi-objective robust optimization [16], info-gap decision theory [17], dynamic adaptive policy pathways (DAPP) [18,19], adaptive pathways [20], and scenario neutral planning [21] or decision scaling [22]. DMDU analytical methods can support rigorous options

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https://doi.org/10.1016/j.rser.2020.109910
Received 10 October 2019; Received in revised form 28 April 2020; Accepted 7 May 2020
Available online 30 July 2020

List of abbreviations

capex	capital expenditure
CMIP5	Coupled Model Intercomparison Project, Phase 5
DAPP	dynamic adaptive policy pathways
DMDU	decision-making under deep uncertainty
GCM	global circulation model
GWh	gigawatt hours
HPC	high performance computing
IRAS-2010	Interactive River and Aquifer Simulation-2010
JICA	Japan International Cooperation Agency
kWh	kilowatt hours
m^3/s	metres cubed per second
Mm^3	millions of metres cubed
MORDM	multi-objective robust decision making
MW	megawatts
NEA	Nepal Electricity Authority
NPV	net present value
PRIM	Patient Rule Induction Method
RDM	robust decision making
ROR	run of river
SWAT	Soil and Water Assessment Tool
UAHP	Upper Arun hydropower project
US$	US dollars
US$bn	billions of US dollars
US$M	millions of US dollars
WEAP	Water Evaluation And Planning

appraisal to understand vulnerabilities and help mitigate risks to satisfactory performance within a water resources system [20,23–25].

Solutions are framed by the way problems are defined, so iterative, stakeholder-informed processes of deliberation have potential to facilitate the emergence of more consensual and ultimately successful strategies [4,26–28]. Consensual generally means developing and using a shared understanding of the system to identify candidate solutions [29]. Success should be stakeholder-informed and defined specific to the context, but often involves no- or low-regret interventions and maintaining diverse options for future adaptation to changing conditions [30].

Linking system impact simulation models to many-objective search algorithms [31] can help move towards a shared perspective on the intervention options that perform well within a system and the trade-offs they imply [4,31,94]. Many-objective simulation-optimization for DMDU has been applied largely in water resources management in developed countries, at regional [32–36] and city [15,37–39] scales. Reservoir operations [40,41] and lake water quality management [42] have also been the subject of such approaches. Both Giuliani et al. [40] and Salazar et al. [41] evaluate changes in reservoir operations and consider hydropower, but not infrastructure system design. Geressu and Harou [43,44] consider multi-reservoir system design including hydropower on the Nile, but do not consider deep uncertainties.

This paper contributes a novel multi-method, stakeholder-driven DMDU approach to hydropower system design, including collaborative, and many-objective methods and comprising four phases: 1) system and performance metric characterization, 2) uncertainty identification, 3) robust optimization with multiple criteria, and 4) stress testing. This approach builds on the robust decision-making framework [14] with regards to identifying metrics and uncertainties with stakeholders and collaborative modelling. It utilizes bottom-up decision-scaling [22] methods for defining hydrological scenarios and implements the extended version of multi-objective robust decision making (MORDM) [39] where multiple scenarios are embedded into a single robust optimization. In a methodological innovation, a post-optimization stress test is added similar to Ray et al. [23]. This considers a wider sampling of the uncertainty than was considered in the robust optimization, to indicate whether an intervention (of new hydropower assets and/or operating rules) selected in phases 1–3 is sufficiently robust to be acceptable to decision-makers or which vulnerabilities might need to be mitigated. Overall, the approach facilitates:

- analysis of the most efficient trade-offs between benefits implied by different interventions (combinations of assets and/or operating rules) in a water resources system,
- identification of asset portfolios robust to future uncertainties,
- quantification of the financial costs (expressed as maximum net present value (NPV) regret) of balancing hydropower generation with other water-dependent benefits in a river basin.

Bhave et al. [20] note the paucity of DMDU methods demonstrated in developing countries. The approach proposed here is demonstrated in Eastern Nepal's Koshi River basin (roughly 10% of Nepal's land surface) to address the future (i.e. 2050s) hydropower system design challenge. The most efficient investments must be identified to make best use of limited financial resources while supporting low carbon economic development for various stakeholder groups under a wide range of plausible climate, social, economic, financial and institutional futures.

The remainder of this paper presents the proposed multi-method approach, the demonstration context, details of the demonstration, and its results. These are followed by a discussion of the method and its results, their implications and conclusions.

2. Approach

A novel four-phased approach for efficient and robust hydropower system design (Fig. 1) is proposed below, addressing investment challenges such as those outlined in Nepal above. These challenges are similarly present in many other countries, to which the approach is also applicable.

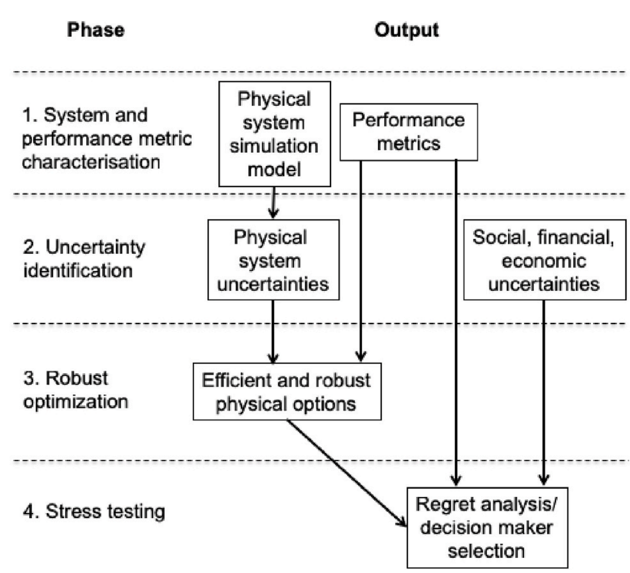

Fig. 1. Process schematic for the proposed four-phased hydropower system design approach, including the outputs of each phase and where they are used in subsequent phases.

2.1. Phase 1: System and performance metric characterization

A river basin (i.e. physical system) simulation model [45–47] is used to evaluate the performance of the system under various physical/environmental conditions and hydropower interventions (new infrastructure and/or operating rules). The simulation model tracks flow and storage over time at points of interest in the river network, outputting decision-relevant summary statistics (i.e. performance metrics) about different aspects of the system's performance at the end of a simulation. Examples of performance metrics could include for example, mean annual hydropower generation, public water supply reliability or environmental impacts. Damming of rivers can be expected to impact on the environment and ecosystems, so it is important to consider relative impacts between different development options in deciding with which to proceed.

Stakeholders from relevant organizations collaborate over an extended period [48] to co-create the physical system simulation model representing their system's most salient features and functions (including non-linearities). Outputs are agreed metrics of system performance most relevant to evaluating the success of proposed interventions. Metrics can be iteratively refined as information provided by the overall analysis increases understanding of and raises new questions about the system's function. Stakeholders must agree that the resulting simulator and metrics provide a sufficiently accurate assessment of impacts, and constitute an agreed and trusted evaluation tool for option testing [49,50]. The physical system simulator does not evaluate all factors in a decision–making process. Physical systems must be analyzed and understood within the context of social and economic systems.

2.2. Phase 2: Uncertainty identification

Quantitative sensitivity analysis is undertaken using the system model developed in Phase 1 alongside qualitative stakeholder consultation aimed at identifying, describing and quantifying the relevant sources of uncertainty for system performance [15,23,51–53]. Holding some model variables constant while varying others helps evaluate which have the greatest influence on outcomes. Multi-factor sensitivity analysis of the existing system under different conditions evaluates the system's sensitivity to future stresses. Phase 2 produces a description of current or proposed assets' vulnerabilities to particular conditions or combinations thereof. Following classical RDM approaches [14], these inform the choice of scenarios or a sampling strategy for the subsequent analysis in phases 3 and 4. In Phase 2 social, economic and financial uncertainties which may be factors in the decision-making process are also identified.

2.3. Phase 3: Robust optimization

A many-objective heuristic search (i.e. optimization) algorithm is linked to the stakeholder-approved physical system simulation model (from Phase 1) to trial, and evolve high performing, interventions [31,41,54–56] from amongst billions of possible combinations. The output of the many-objective search process is not a single optimal solution, but rather a set of options which perform Pareto-optimally, i.e. those for which any further improvement towards one objective (performance metric) would require deterioration of at least one other conflicting objective. These options provide decision-relevant information about multi-dimensional trade-offs between conflicting objectives of performance. They help select interventions which appropriately balance the resulting (monetary/non-monetary) costs and benefits at the performance limits of the system. Technically the options are Pareto-approximate because the many-objective algorithms [31] used cannot be formally proven to converge to a mathematical optimum [31]; they are referred to as Pareto-optimal here to ease discussion.

The search process is undertaken for environmental conditions across an ensemble of plausible futures. The range of future conditions across which an infrastructure portfolio is able (through its potential modes of operation) to provide Pareto-optimal performance indicates its robustness. Robustness metrics (i.e. statistical summaries of performance across the ensemble of future scenarios tested) are informed by stakeholders, analysis of the scenarios to which performance is vulnerable, and stakeholder aversion to the risks of problematic water availability scenarios manifesting [29,57,58]. With the system simulator and metrics of performance and robustness agreed upon, the set of best intervention options identified by the search will be of interest to stakeholders. They then select one or more alternatives via visual analytic plots [59–61] to be stress tested in Phase 4.

2.4. Phase 4: Stress testing

One or more interventions of interest to decision makers from Phase 3 are analyzed using a scenario identification method [62] which identifies the combinations of uncertain conditions which cause the system to fail decision makers' performance thresholds. Failure scenarios can be compared with available evidence to determine if stakeholders deem risks high enough to hedge against [23–25]. If they are, other promising alternative interventions may be stress tested to seek a satisfactory likelihood of failure according to the criteria defined. Otherwise the selection of an efficient and robust investment portfolio is complete.

3. Demonstration of the approach in Nepal's Koshi Basin

This section first describes the context used to demonstrate the approach before describing the details of how each phase was executed.

3.1. Context

Government of Nepal interest in exploring options for hydropower development in the Koshi Basin despite climatic and other uncertainties instigated the development of the approach demonstrated here [63]. Nepal's electricity demand is relatively constant throughout the year. Its generating capacity is limited in the dry season (November to May) by low river flows, because of its reliance on run-of-river (ROR) hydropower. The electricity supply-demand gap was about 410 MW in November 2013, when peak demand reached 1201 MW, resulting in load shedding (i.e. blackouts) of up to 12 h per day [64]. Lack of grid electricity is a barrier to improving living standards, raising productivity and incomes, and helping Nepal's youth transition from agricultural to non-agricultural employment. Electrification also became a policy priority because of concerns about the impact of biomass burning on indoor air pollution and therefore health [65,66]. Note that since this study was undertaken, grid interconnections with India and promotion of private generation among other measures, have allowed Nepal to successfully alleviate some of these challenges [67].

Limited domestic electricity generation capacity, and one of the world's largest potential hydropower resources [68] are confounded by uncertainties around a range of environmental and financial factors affecting demands and the ability to meet them within the lifetime of proposed infrastructure investments. In this context the most efficient investments need to be identified to make best use of limited financial resources while supporting low carbon economic development for various stakeholder groups under a wide range of plausible climate, social, economic, financial and institutional futures.

To demonstrate the proposed approach to hydropower system design, we use a portion of Nepal's Koshi Basin (Fig. 2) which is well suited to hydropower development owing to its steep terrain and substantial water resources yield. Of three main tributaries within the case study area, the Arun River has the highest average discharge at around 200 m^3/s, making it a good prospect for developing ROR hydropower with lower seasonal power yield variation [23]. There are 5 existing

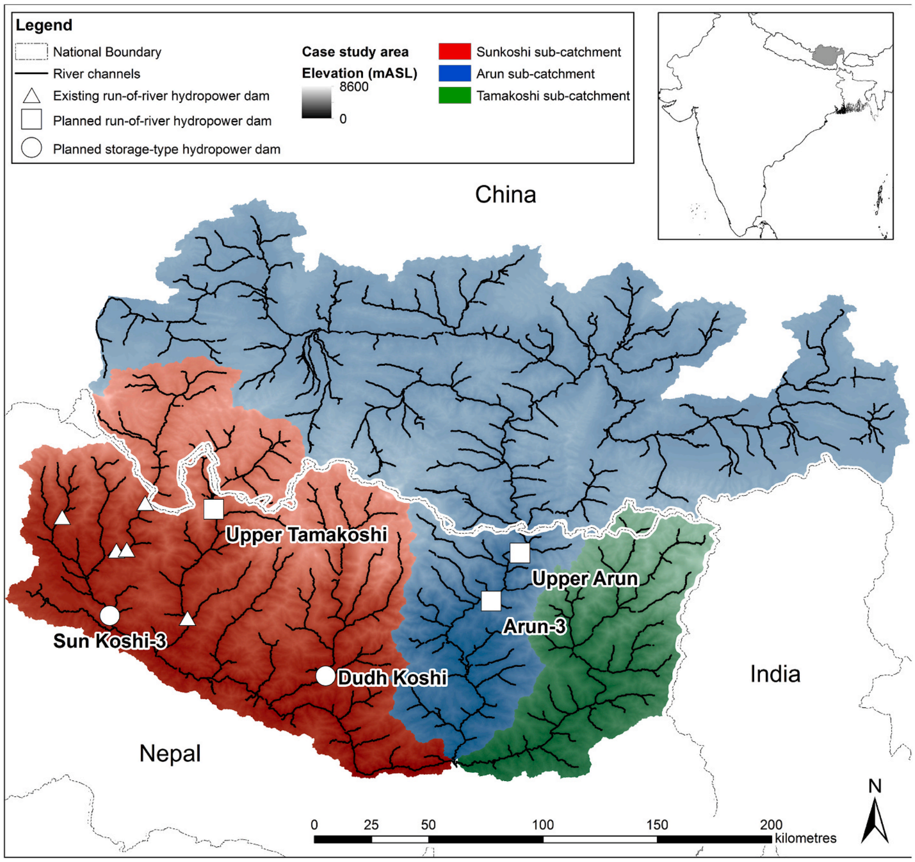

Fig. 2. Location and elevation of the portion of the Koshi Basin modelled for this study, extending beyond Nepal's national boundary and flowing generally south towards its confluence with the Ganges in India. Existing and proposed hydropower dam locations are shown – five of the most favored proposed dams are labelled and included as options in the system model.

small-scale ROR hydropower dams, but little other development of any kind has occurred in the Basin.

A storage-type hydropower masterplan [69] prioritized 10 schemes across the country, two of which are in the area considered here. The master plan recommended that climate change impacts be considered at a later stage, rather than as an integral part of the selection process as proposed here. The proposed approach could help identify more robust investment choices given uncertainties around future Himalayan climate [70–72].

3.2. Phase 1: System and performance metric characterization

An Interactive River-Aquifer Simulation (IRAS-2010, [45]) Koshi River basin model was built and refined in consultation with stakeholders to represent the physical system. Topology, abstraction demand and flow data included in Soil and Water Assessment Tool (SWAT, [73]) and Water Evaluation And Planning (WEAP, [74]) models developed by Chinnasamy et al. [75] were used.

The model includes sub-catchment inflows and abstraction demands spatially located upstream and downstream of existing and proposed hydropower dams following Chinnasamy et al. [75]. Table 1 shows the generating capacities of existing hydropower schemes and capacities plus other characteristics of five of the most favored of those proposed, included as options in the model (Fig. 2). Capital costs were based on locally available estimates rather than calculated. Where a storage dam is included in the model, its operating rules are represented by a piece-wise linear storage-dependent release curve (Fig. 3).

Following Hurford and Harou [76], interpolation between the 3 labelled points dictates dam release at each model time step. Points can be moved in the directions indicated by arrows to vary operation, although point B must always relate to a higher stored volume than point C.

Table 1
Existing and proposed hydropower projects included in the IRAS-2010 model.

	Project name	Type of scheme	Generating capacity (MW)	Capital cost (US $M)
Existing	Sunkoshi HEP	Run-of-river	2.5	N/A
	Baramchi HEP	Run-of-river	4.2	N/A
	Indrawati III	Run-of-river	7.5	N/A
	Khimti	Run-of-river	60	N/A
	Bhote Koshi	Run-of-river	45	N/A
Proposed	Sun Koshi 3	Storage	536	1690.5
	Dudh Koshi	Storage	300	1144
	Upper Tamakoshi	Run-of-river	456	441
	Upper Arun	Run-of-river	335, 750, 1000, 1355 or 2000	446–2600 depending on gen. capacity
	Arun-3	Run-of-river	900	423.2

The modelled storage volume of proposed storage dams follows NEA & JICA [69]. In the case of the ROR Upper Arun hydropower project (UAHP), five mutually exclusive generating capacity options are included. This leads to nine individual dam investment options and 95 possible combinations thereof; with the available unique interventions growing into the billions when differing operating rules are considered

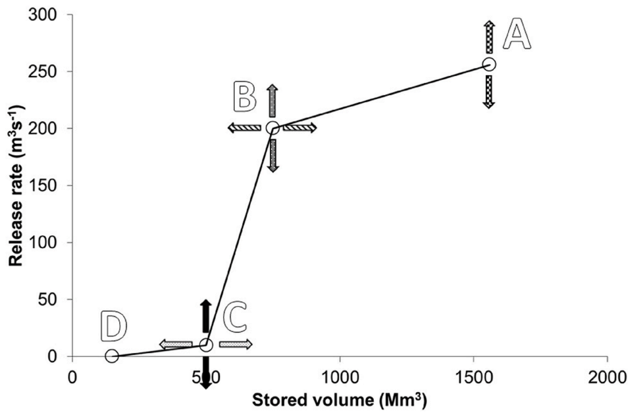

Fig. 3. Example storage dependent release rule curve. Coordinates of the 3 labelled points (A–C) control dam release at each model timestep. Opposing, same-patterned arrows show directions of possible alteration. Point B stored volume must always be higher than Point C stored volume.

for the storage dams.

The following model performance metrics were defined based on discussions with stakeholders and a desk study of salient issues in the basin and nationally:

1) capital expenditure (capex) (US$M)
2) dry season electricity generation (Dec–April, GWh)
3) total annual electricity generation (GWh)
4) firm electricity generation with 99.5% reliability (GWh)
5) urban water deficit (Mm^3/year)
6) irrigation deficit (Mm^3/year)
7) flood peak at the basin outlet (m^3/s)
8) number of environmental flow failures downstream of dams (occurrences)

Looking beyond the physical water system, net present value (NPV) of investments was recognized by stakeholders as an important metric in selecting between them. NPV depends on levels of hydropower generation (evaluated by the water system model), but also economic and financial factors outside the scope of the physical model: discount rate, electricity price, asset lifetime, total capex and operation & maintenance costs.

Associated with NPV, the maximum regret of implementing any investment was of interest to decision makers. Maximum regret, measured in terms of NPV, is a metric that quantifies the financial robustness of an intervention.

The concept of regret is defined by Savage [77] as the difference between the performance of a strategy (e.g. investment portfolio) in some future state of the world, given some value function (e.g. NPV), and that of what would be the best-performing strategy in that same future state.

For a set of portfolios *P*, the regret of a portfolio *i* in the set *P*, in the future state of the world *s*, is therefore expressed as:

$$regret(i,s) = \max_{i' \text{ in } P}(performance(i',s)) - performance(i,s) \quad \text{(Eq. 1)}$$

As we express regret in terms of net present value (NPV), the regret of portfolio *i* across all future states of the world *s* can be expressed as:

$$\mathrm{regret}(i) = \max_{s}(-NPV(i,s)) \quad \text{(Eq. 2)}$$

Investment portfolios with lower maximum regret across a wide range of possible futures are more desirable. The regret of portfolio *i* in a future state of the world *s* is defined by:

$$\mathrm{regret}(i,s) = \max_{i'}(NPV(i',s) - NPV(i,s)) \quad \text{(Eq. 3)}$$

The best option is the one that solves:

$$\min_{i}(\max_{s}(\boldsymbol{regret}(\boldsymbol{i},\boldsymbol{s}))) \quad \text{(Eq. 4)}$$

3.3. Phase 2: Uncertainty identification

Uncertainties were considered which could impact the performance of infrastructure up until 2050. Preliminary identification of relevant uncertainties was completed through workshop exercises in Nepal and subsequent contacts with Nepal Electricity Authority (NEA) and other stakeholders. Sources of uncertainty considered significant in relation to water availability for hydropower generation were river flows, abstraction demands and environmental flow releases. Further economic and financial sources of uncertainty, affecting NPV, included construction cost, discount rate, plant lifetime and seasonal wholesale electricity price.

Modelling confirmed the sensitivity of hydropower generation to environmental flow releases, flow conditions and changing upstream abstraction demands, so these were accounted for in the Phase 3 search.

Hydropower generation depends on river discharge, which varies both seasonally and inter-annually. Climate change introduces uncertainty about statistical changes in flows to this existing variability. Model input climate change flow scenarios were generated in two stages: 1) a bottom-up analysis of temperature and precipitation change impacts on Arun River flows to the site of the proposed Upper Arun hydropower project (UAHP) dam [23], 2) five percentage change factors (−10, +7.5, +25, +42.5 and + 60%) were sampled from across this UAHP flow data as in Decision Scaling [22], extending the range of changes implied by CMIP5 global circulation model (GCM) outputs. These were then applied to baseline (1971–2000) flows from Chinnasamy et al. [75] for inflow locations across the basin.

Abstractions for agricultural and urban demands can both affect and be affected by hydropower dams depending on whether they are located upstream or downstream respectively. Present day demands from Chinnasamy et al. [75] were used and these were also increased by 50% in line with future population projections for Nepal by 2050 [78]. These two scenarios are considered extremes of abstraction demand uncertainty.

A hydropower scheme designed with no consideration of environmental flow releases which is later subject to such a requirement, will suffer from a reduction in generation and so return on investment. Two scenarios were applied, representing release requirements at ten per cent of the minimum monthly average discharge in line with Nepal's Hydropower Development Policy [79], or no requirement, which also represents lack of enforcement.

3.3.1. Economic and financial uncertainties

Economic and financial parameter uncertainties were considered in the Phase 4 stress test as they are not physical system uncertainties represented by the system modelling and search.

Delays in the implementation of hydropower investments can lead to cost increases [80,81]. Final capex for Nepal's Marshyangdi Dam were exceptional at three-times higher than expected, so this 300% was considered an upper bound for a range of plausible capex with a lower bound of the expected costs.

A higher discount rate prioritizes present needs and a lower discount rate emphasizes sustainability [82]. The balance struck between these competing interests can lead to dissatisfaction amongst some stakeholders [83]. The World Bank typically uses discount rates of 10%–12%, but the appropriate rate can vary for a given application [84,85]. In this study, a high discount rate reduces the relative benefits of optimal plant operation – after 25 years, the additional value generated from optimal vs. standard operation becomes negligible after discounting. After consultations with NEA a range from 3 to 12% was chosen to explore the impact of varying short-term or long-term objective prioritization.

The range of power plant lifetimes accounts for different options of sediment management and sediment damage to turbines through abrasion, and potential seismic structural damage. Sediment management practices such as catchment slope stabilization or stilling basins can increase a plant's lifetime compared to where no mitigation of sediment damage occurs [86]. It is unknown what type of shock might cause dam failure given an unknown quality of construction. Plant lifetime of up to 36 years was considered, as after this period the discount rate makes economic benefits negligible.

The electricity price currently varies between the wet and dry seasons by a factor of 2. The price could vary further if the Government of Nepal were to export electricity to India; in this case it was considered it could increase up to 0.135 US$/kWh [87,88].

3.4. Phase 3: Robust optimization

In the Koshi Basin there are $>10^{20}$ possible combinations of new assets built and their operating rules but the search algorithm required only one million trial simulations to converge on the highest performing (Pareto-optimal) intervention options. The model built in Phase 1 completes a simulation of 30 years at monthly time step in less than 1 s, facilitating the completion of one million simulations on high performance computing (HPC) clusters with multiple processors in a practical timescale (e.g. 24–36 h). The search algorithm used here was the Epsilon Dominance Nondominated Sorted Genetic Algorithm-II (ε-NSGAII) [89]. The algorithm was parameterized according to recommendations of Kasprzyk et al. [54]. A random seed trial [55] was applied to test the sensitivity of solutions to the randomly generated initial decision variables.

3.4.1. Problem formulation

The multi-objective search or 'optimization' problem is formulated as the following question: Given conflicts between some of the following objectives, what combinations of assets and their operating rules (Fig. 3) minimize urban water supply deficits, capital expenditure, agricultural water supply deficit, maximum flood peak at the basin outlet, and environmental flow failures downstream of dams while simultaneously maximizing dry season electricity generation, total annual electricity generation and firm electricity generation? Mathematically:

$$Minimise\ \mathbf{F}(\mathbf{x}) = \left(f_{ud} f_{capex} f_{ad} f_{flood,} -f_{dry,} -f_{tot,} -f_{firm} f_{env}\right) \quad \text{(Eq. 5)}$$

$$\mathbf{x} = \{Y_i, Z_j\}$$

$$Y_i \in \{0,1\} \forall_i \in \Omega$$

where $\mathbf{x}$ is a vector representing an intervention of new hydropower dams and their operations (for storage-type dams), Y_i is a binary variable representing the inclusion of dam i in intervention $\mathbf{x}$ (1 means the dam is included, 0 means not included), Z_j is the release rule of storage dam j.

$$f_{ud} = \frac{1}{Y}\sum_{y=1}^{Y}\left(\sum_i Deficit_y^i\right) \quad \text{(Eq. 6)}$$

where y is the year in the time horizon, Y is the total number of simulated years, i is an urban demand and $Deficit_y^i$ represents deficit experienced by urban demand i during year y.

$$f_{capex} = \sum Capex_i \quad \text{(Eq. 7)}$$

where $Capex_i$ is the capital expenditure associated with each new dam i in the portfolio of infrastructure.

$$f_{ad} = \frac{1}{Y}\sum_{y=1}^{Y}\left(\sum_i Deficit_y^i\right) \quad \text{(Eq. 8)}$$

where y is the year in the time horizon, Y is the total number of simulated years, i is an agricultural demand and $Deficit_y^i$ represents deficit experienced by agricultural demand i during year y.

$$f_{flood} = Maxflood \quad \text{(Eq. 9)}$$

where *Maxflood* is the highest flow recorded at the outlet of the model basin during the simulation.

$$f_{dry} = \frac{1}{Y}\sum_{y=1}^{Y}\left(\sum_{m=12}^{4}\left(\sum_i Generation_y^i\right)\right) \quad \text{(Eq. 10)}$$

where y is the year in the time horizon, m is the month where January is 1 and December is 12, Y is the total number of simulated years and $Generation_y^i$ is the generation at dam i in year y.

$$f_{tot} = \frac{1}{Y}\sum_{y=1}^{Y}\sum_i\left(Generation_y^i\right) \quad \text{(Eq. 11)}$$

where y is the year in the time horizon, Y is the total number of simulated years and $Generation_y^i$ is the generation at dam i in year y.

$$f_{firm} = LowGen \quad \text{(Eq. 12)}$$

where LowGen is the 0.5th percentile value of monthly total energy generation during the simulation.

$$f_{env} = \sum_i MinFlowFailure_i \quad \text{(Eq. 13)}$$

where $MinFlowFailure_i$ is a failure to achieve the minimum environmental flow downstream of dam i.

Decision variables are numerical values within the system model which are varied to represent interventions. The search algorithm varies and mixes sets of these values to iteratively develop the best combinations of investments and operating rules. There are 31 individual decision variables in the Koshi Basin model:

- Binary build/no build decision for each of nine proposed dams (Table 1).
- Five storage dependent release rule coordinates, for each of two seasons and each of two storage dams (Fig. 3). Maximum release rates from each of the two dams were limited to 1500 m^3/s.
- Two dates controlling timing of the two storage dam release rule seasons (allowing different rules for wet/dry season operation, for example).

Each decision variable has a range of possible values and there are some mutually exclusive combinations, but the storage dependent release rules have large ranges of coordinates (i.e. storage and release values) and therefore large numbers of possible combinations. Storage capacities are fixed according to published designs [90].

3.4.2. Searching for efficiency and robustness

All combinations of 5 river flow scenarios, 2 environmental flow release scenarios and 2 abstraction demand scenarios were considered, leading to 20 unique physical conditions scenarios. To identify robust infrastructure investment portfolios, three many-objective heuristic search processes were conducted; 1) on average across all 20 scenarios, 2) under high water availability conditions for generating hydropower, and 3) under low water availability conditions for generating hydropower (Table 2). This approach confirmed whether portfolios which performed efficiently and robustly on average could also be operated efficiently to take advantage of opportune high water availability and/or to maintain efficient performance under adverse water availability. Each of the three searches applied the same problem formulation for 'identification of alternatives' [29].

Table 2
Uncertainties associated with three searches used to explore robustness.

	Resulting conditions		
Uncertainties	**High water availability**	**All**	**Low water availability**
−10% flows		X	X
+7.5% flows		X	
+25% flows		X	
+42.5% flows		X	
+60% flows	X	X	
No Environmental flow release	X	X	
Environmental flow release		X	X
No abstraction demand increase	X	X	
Abstraction demand increase		X	X

3.5. *Phase 4: Stress test*

Stress testing in this demonstration used positive net present value (NPV) of an intervention as the success criterion. Multiple combinations of economic and financial parameters and conditions were statistically sampled using Latin Hypercube Sampling to generate 150 futures covering the uncertainty space efficiently [91]. Equal probabilities were assigned to values within each uncertainty range described in Section 3.3.1. These were applied as inputs to calculate mean NPV, the conditional standard deviation of NPV and the maximum NPV regret (i.e. relative risk) associated with each intervention option identified in Phase 3. Mean and conditional standard deviation of NPV evaluate the range of performances by an intervention, whereas the maximum regret compares performance between interventions.

Various analytical methods can then be applied; here a scenario discovery method called Patient Rule Induction Method (PRIM) [92] was used to identify potential failure scenarios for a selected intervention.

4. Summary

Fig. 4 summarizes the implementation of each Phase of the approach for this demonstration.

5. Results

5.1. *Efficient options*

Investment options for increasing dry season electricity generation - Nepal's immediate challenge – are reported on first. Fig. 5 shows Pareto-optimal (i.e. efficient) intervention options for increasing dry season energy generation. Each point represents a unique intervention (a portfolio of dams and their operating rules) identified by one of the three searches (indicated by the shape of the point).

Points from each search form separate efficiency frontiers (sets of the most efficient interventions). All points represent 'least cost' options for increasing electricity supply - the criterion for traditional electricity generation infrastructure selection – where a demand level to meet has not been pre-specified. Diminishing returns are shown by the flattening of the three curves moving from low to high capex. Without considering any further information as in sections below, investing up to a point before returns start to diminish, e.g. around US$1.5bn, makes sense.

Options requiring equal capex comprise identical asset portfolios but different operating rules. Four illustrative dotted lines in Fig. 5 shows examples where options have the same capex/asset composition but perform differently depending on the water available and how they are

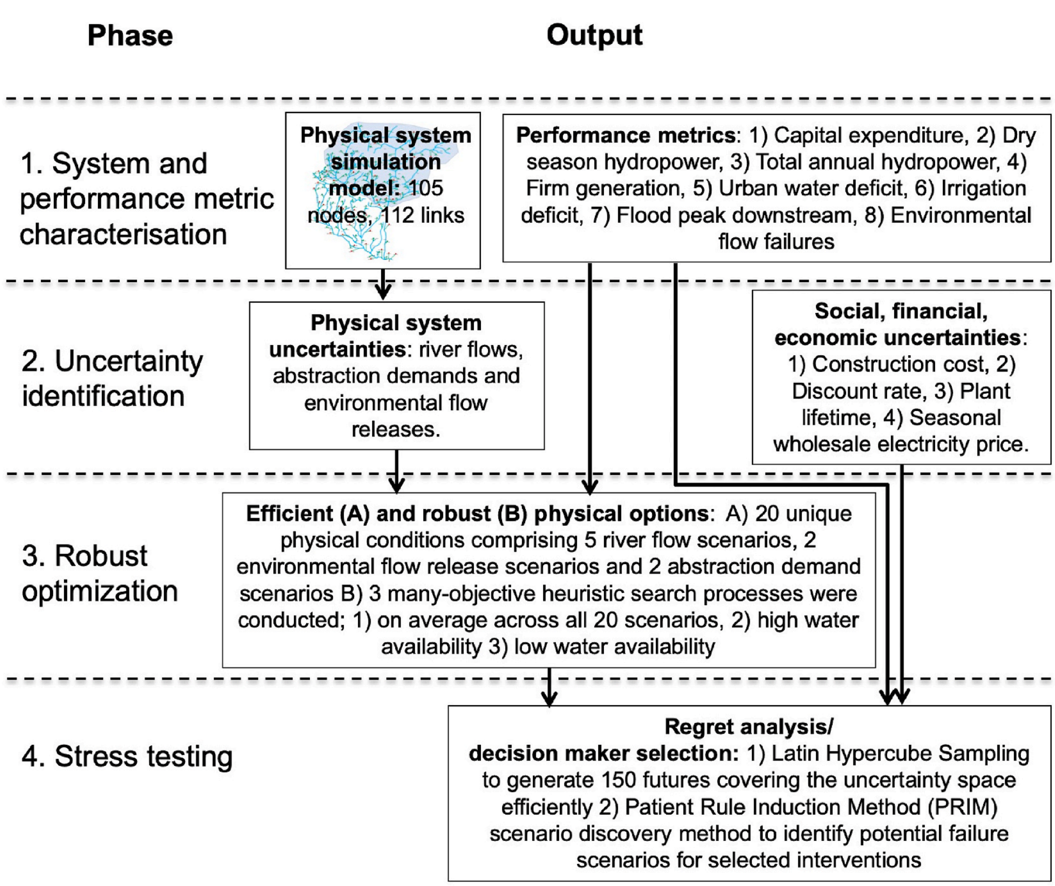

Fig. 4. Process schematic of the demonstrated implementation of the proposed approach shown in Fig. 1.

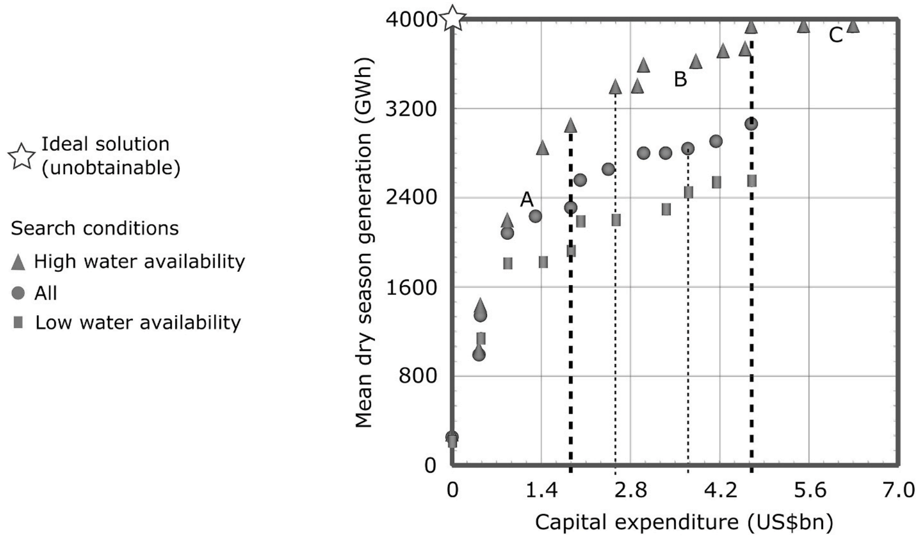

Fig. 5. Efficient options for increasing dry season electricity supply under three scenario conditions. Points along the same dotted line represent varying performance of the same infrastructure portfolio, owing to different water availability conditions and operations (of storage dams where included). Labelled options indicate examples of a portfolio performing Pareto efficiently only under some search conditions (one or two of the three). Thick dotted lines indicate portfolios considered robust in this analysis as they perform efficiently across all three search conditions.

operated. Asset portfolios and operating rules efficient across all tested scenarios (circles) do not necessarily perform efficiently under high and low water availability conditions. The circular point labelled A for example, does not have a corresponding triangular or rectangular point of equal capex. This means its component assets cannot be operated Pareto-optimally under high or low water availability Similarly, labelled points B and C represent investments which can be operated efficiently under high or low water availability conditions respectively, but not across the plausible range of conditions. Dry season generation correlates with firm energy and total annual energy generation, so results in Fig. 5 represent efficient investments in terms of US$/GWh for energy generation more broadly. Note that the high and low water availability represent extremes of combined climate, abstraction demand and environmental regulation, so these represent plausible bounds of system performance.

5.2. Selecting amongst efficient options for robustness

For this demonstration, robust portfolios for least-cost generating capacity expansion were considered to be those which can be operated efficiently (as defined by the search processes described above) under all three search conditions (see examples along thick dotted lines in Fig. 5). Searching for such portfolios identifies 6 unique combinations of assets, including the existing configuration with no new dams (and therefore no capital expenditure).

In addition to interventions identified as both efficient and robust for energy generation and investment, decision makers may appreciate a broader perspective on efficient and robust options in relation to all eight system performance objectives. Fig. 6a shows the number of efficient and robust intervention options increases when changing from least-cost generating capacity expansion (thick lines/large points) to analysing efficiency and robustness in relation to all eight system performance objectives (thin lines/small points). There are 19 unique portfolios (including the status quo) considering efficiency and robustness for all metrics. Decision-relevant information about trade-offs between objectives is increased and the incremental differences in performance between portfolios are reduced. Decision makers are more likely to find a balance of performance which suits their preferences, and the new information may influence these preferences. Different methods of visualisation can provide different perspectives on the results. Fig. 6b uses a scatter plot to illustrate an inflection point in the relationship between mean annual generation and environmental flow failures. Such 'tipping points' could be informative of rational limits to development where environmental impacts are a concern, for example. They are not so easily understood from parallel axis plots as in Fig. 6a however.

Fig. 6 classifies interventions by portfolio composition in relation to ROR and storage type dams. Use of storage type dams increases the range and variety of performance available because of their greater flexibility of operation, with two storage dams (red lines/points) maximizing the options. Note that all 'thin line' options in Fig. 6 include one or both storage dams. Where one storage dam is used, this is Dudh Koshi.

5.3. Considering regret to differentiate between investment portfolios identified as efficient and robust

Various approaches could be used in conjunction with stakeholders to select a portfolio for investment from amongst the efficient and robust ones identified by the Phase 3 physical system search. In this case the maximum regret associated with each of the interventions identified in Phase 3 was analyzed, in terms of net present value (NPV). The maximum regret associated with the current situation (i.e. No development) is relatively high within the results dataset, indicating opportunities exist to increase financial returns through investment. NPV for the current situation is non-zero as there are small existing ROR schemes already in operation. Some interventions with only storage dams have higher maximum regret than the 'do nothing' option, because of their high capex and low financial returns, making them potentially unattractive unless their non-monetary benefits are considered to outweigh the financial risks. The class of interventions which include the two storage dams combined with ROR dams has the greatest operational flexibility (as shown by the wide variety of efficient and robust performance outcomes, Fig. 6a). The lowest maximum NPV regret of this class is over twice as large as the overall lowest maximum NPV regret option however. This means returns on investment may be compromised by prioritizing benefits such as environmental flows or flood peak reduction. The operational flexibility of storage dams (Fig. 3) allows them to be used for controlling the balance between monetary and non-monetary benefits. Readers are invited to interactively explore the parallel plot results dataset themselves at: http://www.polyvis.org/sheet/pvpUcLZ4Vf, making use of the 'Using Polyvis' link included, and noting that colors are applied separately to Figures here for emphasis.

5.4. Identifying failure modes of a preferred portfolio

To illustrate the information outputs from the Phase 4 stress test phase a high NPV, low maximum NPV regret intervention was selected (indicated in Fig. 7). It comprises Dudh Koshi storage dam and the Upper Arun (335 MW) and Arun-3 ROR dams. It was selected as having low

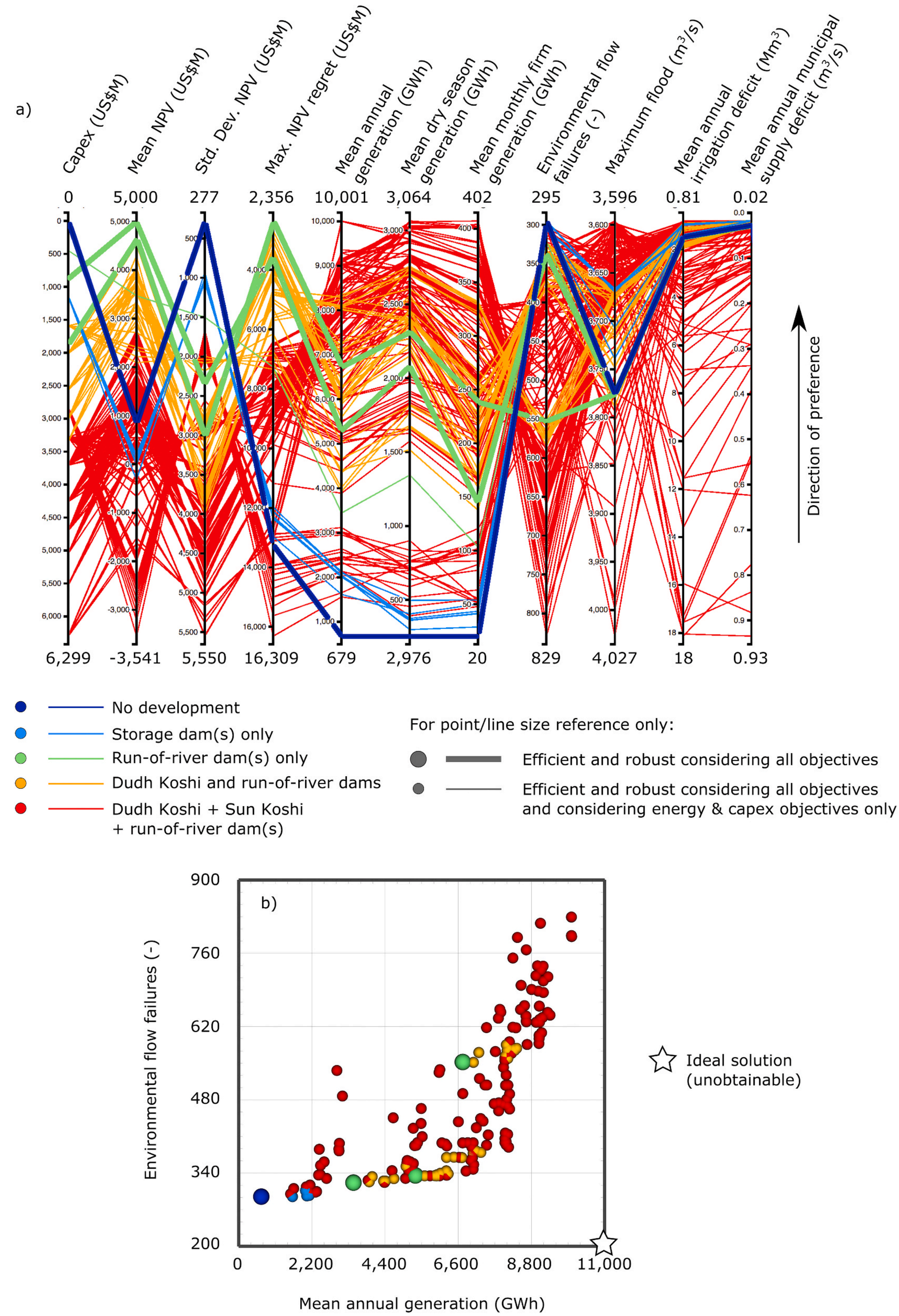

Fig. 6. a) Parallel axis plot of robust and efficient portfolio performance defined for all eight search objectives and stress testing output NPV statistics. Each line represents an intervention portfolio which met the Phase 3 efficiency and robustness criteria. Better performance occurs at the top of the plot, so a perfect intervention would be a straight line across the top. Line colors indicate classes of infrastructure portfolio composition. Thick lines represent efficient and robust performance when only generation and capex are considered. Thin lines represent efficient and robust performance considering all the metrics b) Scatter plot showing an inflection point in the performance frontier between mean annual generation and environmental flow failures, illustrating non-linear interaction between objectives. Environmental flow failures increase at a greater rate per GWh of additional mean annual generation beyond approximately 7500 GWh. This could be a rational point at which to limit development in the basin, if the associated increase in flow failures from the 'No development' option is acceptable. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

maximum NPV regret (US$3,024 m) but higher dry season generation, environmental flow and flood peak performance than the lowest maximum NPV regret option (US$2,356 m), for similar capex. Trade-offs would be necessary in other objectives but could be attractive to decision makers. This intervention was tested via a scenario discovery analysis to find the conditions under which it could fail. The threshold for success or failure was defined as zero NPV.

The failure scenario identification analysis revealed a combination of two conditions causes the selected intervention's NPV to be negative. The two conditions are: capex increase of greater than 14% and wet season electricity prices remaining below 0.087 US$/kWh. Of the 33 futures with these conditions, for the selected intervention the NPV is negative in 16. This combination is a strong predictor as it exists in 15 of the total 16 futures in which the intervention is not profitable. Further scenario discovery analysis, beyond the scope of this work, would reveal additional sets of conditions that explain the remaining failures, which policy makers could weigh against additional evidence. Nevertheless, this single set of conditions offers useful information for a policy dialogue on the potential vulnerabilities of the selected intervention or its asset portfolio.

6. Discussion

The approach proposed here demonstrates the utility of combining DMDU techniques appropriately to address investment decisions in the presence of multiple uncertainties. This is the first example of combining many-objective trade-off analysis with DMDU methods for hydropower system design. Earlier studies considered hydropower generation as a criterion in DMDU reservoir operation analysis [40,41] or multi-reservoir system design including hydropower but excluding multiple uncertainties [43,44].

Results identified a set of the best available hydropower system

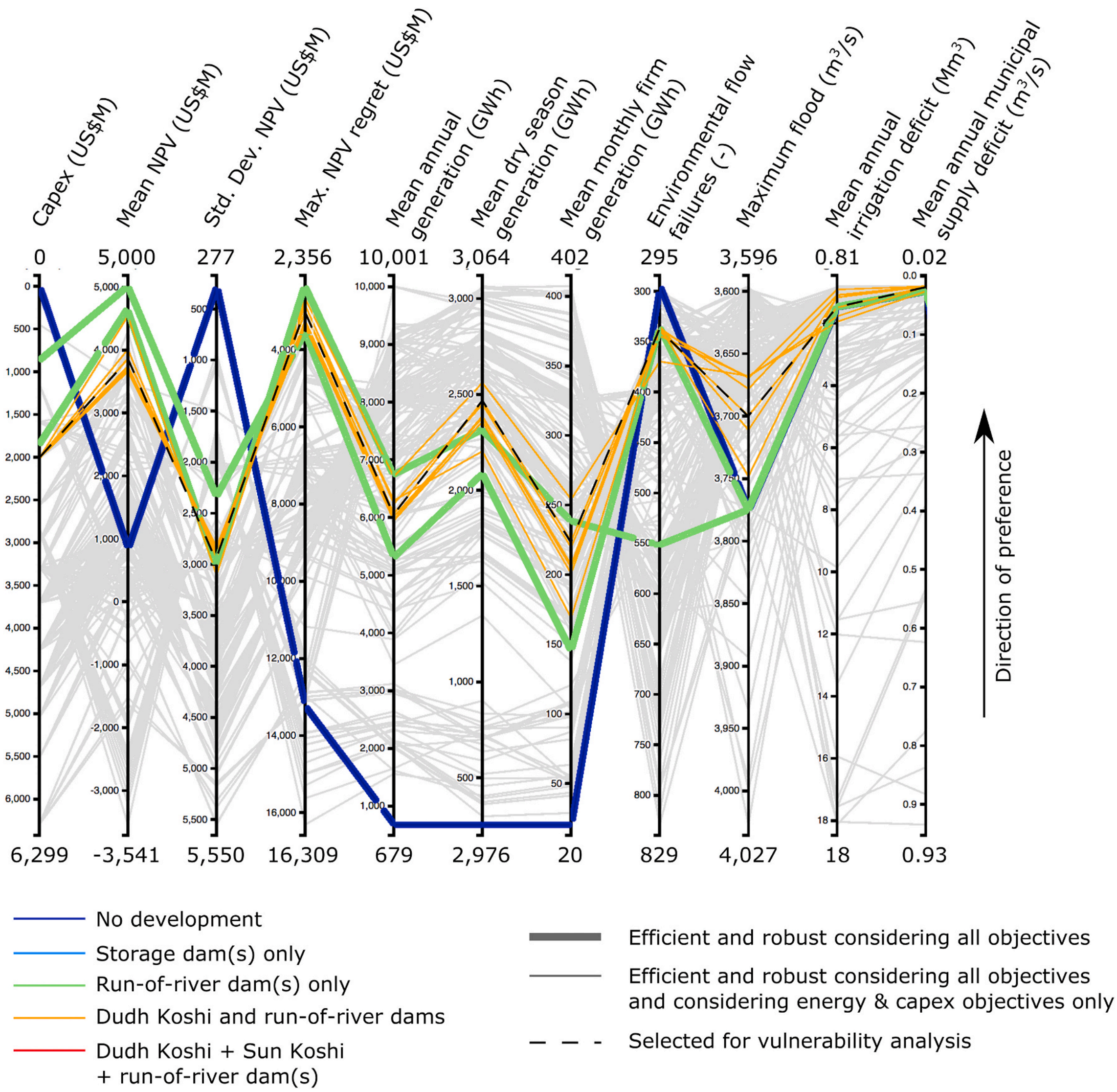

Fig. 7. Parallel axis plot of selected robust and efficient portfolio performance defined for all eight search objectives and stress testing output NPV statistics. Non-selected performances are shown in grey. Selection is on the basis of high mean NPV and low maximum NPV regret. By compromising from the lowest maximum NPV regret option (US$2,356 m), to US$3,024 m, critical dry season generation could be increased along with performance for environmental flow and flood peak reduction. Trade-offs would be necessary in other objectives but could be acceptable to decision makers. The no development option is shown for reference. Infrastructure portfolio composition (color) is classified as in Fig. 6 to illustrate how composition relates to the variables plotted. NPV is highest where hydropower generation is prioritized by operating rules, as hydropower is the sole revenue generating source considered. NPV is more vulnerable to high regret where hydropower revenue is lower. Prioritizing non-revenue benefits decreases return on investment and risks to return on investment. The indicated intervention option was selected for stress testing vulnerability analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

interventions to address multiple system performance goals and uncertainties. These can be differentiated by considering both the balance between benefits provided and the conditions which could threaten their delivery. In this case a promising intervention of one storage-type and two ROR dams in the Koshi Basin was shown to be vulnerable to a combination of less than 0.087 US$/kWh wet season electricity price and 14% increase in capex. Decision makers must deliberate whether the balance of benefits and vulnerabilities it provides is attractive, considering the optimization used here can only account for the selected metrics of system performance rather than their more complex human perspectives.

The implications of this for basin development are that both infrastructure selection and operation are important considerations which interact and should be considered simultaneously in strategic system design. Although not considered here, the methods used here are able to identify the highest performing storage capacity for dams or other infrastructure design characteristics [43].

A broader range of performance measures should be used to select between options than in traditional least-cost based capacity expansion analysis. Trade-offs between financial returns on investment and non-monetary benefits such as environmental flows or flood peak reduction must be assessed. These trade-offs quantify multiple opportunity costs, for example to hydropower generation of maintaining environmental flows. This type of information could help inform compensation arrangements where a particular balance of physical benefits is preferred. Hurford et al. [93] demonstrate more sophisticated metrics of environmental performance than applied here, rep-re-sent-ing in-di--vid-ual pro-vi-sion-ing ecosys-tem ser-vices at dif-fer-ent lo-ca-tions and re-lat-ing to dif-fer-ent time pe-ri-ods.

The impact of physical and economic/financial uncertainties on performance should be analyzed to provide decision-relevant information about the robustness of different system configurations and operating modes. The system's ability to capitalize on more favorable future conditions may otherwise be restricted, or assets may underperform against expected returns.

Infrastructure portfolio selection is the primary factor influencing system robustness, as operating rules can be altered according to prevailing conditions or preferences. Portfolios of assets, which perform efficiently and robustly do so with varying degrees of operational flexibility however. Portfolios offering a greater range of efficient performance, balancing benefits in different ways, may be attractive to decision makers owing to their adaptability to changing conditions, preferences or needs. In the demonstration presented here, increased adaptability also increases potential maximum regret; revenue depends on power generation alone and the more adaptable storage dams have greater capex. Maximum regret must be balanced with other considerations in decision-making.

Using NPV as the sole indicator of returns on investment implicitly favors revenue earning generation (i.e. power generation) over other metrics of performance. Environmental and flood control benefits for example, which could also be considered returns on an investment, do not figure in NPV calculations. Prioritizing non-monetary benefits like these increases maximum NPV regret by reducing the revenue from hydropower generation which compensates for capital expenditure. Additional benefits which could be associated with storage dams, such as irrigation schemes were not modelled here, but could add significant value to such schemes, thereby increasing their NPV and decreasing maximum regret. Maximum NPV regret can be affected by the balance of benefits selected as well as uncertainties. Value judgements may therefore have greater impact on system performance than physical or economic/financial uncertainties. Including non-monetary metrics in maximum regret analysis could provide a useful statistic for comparison with maximum NPV regret, but decisions are likely to be taken using this as just one piece of information amongst the many provided by the approach and iterations may be required to explore trade-offs and system robustness further. Decision makers and their priorities will differ substantially between contexts.

This demonstration at river basin scale neglects investment options located outside the basin. Future work could expand the scope of the analysis to include different boundaries for the different systems involved. For electricity this would be the national energy system or even regional (multi-country) system, thus requiring representation of alternative energy sources such as thermal, solar and wind. Such a power system scale analysis would better facilitate a DAPP approach [18] as supply-demand imbalance adaptation tipping points are not relevant at smaller scale.

Twenty physical conditions scenarios were used in this demonstration, but more complex and/or extensive conditions could be used, informed by plausible ranges of uncertainties. Changes to seasonal flow variations could be represented within these scenarios to explore the impact on system performance and robustness. The scenario discovery analysis here was based on the search results from all water availability scenarios for simplicity, but could be expanded to the results from each of the 20 scenarios individually to provide more detailed information. Operating rules of the storage-type dams were also fixed at the beginning of each trial simulation, limiting analysis of the capacity for rules to adapt to changing conditions. Relieving this constraint could help investigate performance over longer timeseries with non-stationary flow characteristics. Adaptation tipping points for changing operating rules could be defined as in DAPP [18].

Increased computing resources or efficient sampling strategies could allow economic and financial scenarios to be included as uncertainties in Phase 3 rather than Phase 4. At present the combinatorial effect is too great, making the problem intractable given the available computing resources. Each additional economic scenario would double the number of scenarios to be simulated, from the current number of 20.

Stakeholder involvement was conducted through workshops and meetings with relevant ministries and development partners in the national capital only for the demonstration reported here. This was linked to budgetary and organizational constraints, but will necessarily limit the relevance of some of the study's results and hence some of its recommendations. Some metrics of performance may be missing and could have been formulated differently to better quantify development impacts on stakeholders.

7. Conclusions

A four-phased multi-method approach was proposed and demonstrated for defining and selecting efficient and robust hydropower system design options (assets and their operations) in collaboration with resource system stakeholders. The design options are efficient in that they optimize performance considering all the possible weightings of the multiple objectives of the resource system. The investment bundles are robust as they perform satisfactorily across a plausible range of future water availability scenarios. Vulnerability to financial uncertainties is assessed through scenario discovery analysis of the NPV and maximum NPV regret analysis. The approach helps decision makers differentiate between designs on the basis of their preferences for balancing benefits and risks.

The approach was demonstrated in an energy-water infrastructure system in Nepal showing the benefits of designs including a diverse set of assets that enable both adaptability to different future conditions and rebalancing future benefits between different water users. The higher capex required to build storage dams, and the sacrifice of some revenue generating activities to provide non-monetized services may make them less financially attractive. The demonstration shows multi-method decision-making under deep uncertainty approaches can be customized to generate valuable insights into the trade-offs implied by robust and efficient infrastructure investment portfolios in energy-food-water systems, and by the impact of combinations of uncertainties on investment performance. The approach is flexible and applicable to any context where efficient and robust future hydropower systems are desirable.

Extending the approach using integrated energy-water system modelling could allow efficient and robust hybrid renewable energy systems to be identified which perform well despite an uncertain future.

Credit author statement

Anthony Hurford: Methodology, Software, Formal analysis, Writing - original draft, Visualisation, Project administration Julien Harou: Conceptualization, Methodology, Writing - original draft, Supervision, Funding acquisition Laura Bonzanigo: Methodology, Software, Formal analysis, Writing - review & editing Patrick Ray: Methodology, Formal analysis, Writing - review & editing Pravin Karki: Conceptualization, Funding acquisition Luna Bharati: Data curation Pennan Chinnasamy: Data curation.

Declaration of competing interest

None.

Acknowledgments

This work was supported by World Bank contract numbers 7175220 (University of Manchester) and 717 4462 (University of Massachusetts) and the UK Economic and Social Research Council (ESRC) through grant ES/P011373/1. The authors acknowledge the use of the Computational Shared Facility of the University of Manchester and associated support services, and Massachusetts Green High-Performance Computing Center (MGHPCC) in the completion of this work. The authors thank Julie Rozenberg for her kind assistance on the study.

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