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RESEARCH ARTICLE
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Key Points:

- Traditional approaches to hydropower planning need to be revisited to account for the impact of a variable climate on turbine efficiency
- Maximizing the benefit cost ratio rather than the net present value promotes smaller designs, better adapted to a drought-prone world
- Socio-economic and climatic factors are both crucial to design financial robustness

Supporting Information:

Supporting Information may be found in the online version of this article.

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Importance of Variable Turbine Efficiency in Run-Of-River Hydropower Design Under Deep Uncertainty

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Abstract When less water is available, hydropower turbines are less efficient, or have to stop altogether. This reality is often neglected in recent work on the planning and operations of hydropower systems, despite widespread expected increases in drought intensity, frequency and duration. This paper is the first to integrate variable-efficiency turbines into a hydropower plant design framework that accounts for design optimization as well as deep uncertainty in climatic and socio-economic variables. Specifically, this framework focuses on leveraging multi-objective robust decision making for the financially robust design of run-of-river hydropower plants, whose output is highly sensitive to flow variability. Application to five plants in Türkiye challenges two key design assumptions, use of net present value as a design objective and use of identical turbines. Instead, maximizing the benefit-cost ratio yields plants with better financial viability over a range of plausible futures. They tend to have smaller capacity, and feature a small turbine that is well-adapted to low-flow periods. Another key insight is that socio-economic uncertainties have as much or even more impact on robustness than climate conditions. In fact, these uncertainties have the potential to make many small hydropower projects too risky to build. Our findings are of considerable practical relevance at a time where 140 GW of unexploited small hydropower potential could help power the energy transition. They also highlight the need for similar research in reservoir-based plants, considering over 3,000 such plants planned or in construction worldwide.

1. Introduction

Droughts are among the most damaging natural disasters globally, with dramatic impacts on ecosystems, agriculture, water supply, and socioeconomic systems (Dai, 2011; Field et al., 2012). Observations from the Global Precipitation Climatology Center (GPCC) have revealed positive trends in the frequency, length, and intensity of meteorological droughts in many regions including Mediterranean, Central Africa, Amazonia, North-Eastern China, and Southern Australia between 1951 and 2010 (Spinoni et al., 2014). In addition, numerous scientific studies and reports show that due to global heating, droughts are expected to be more frequent, severe, and long-lasting in the future than in prior decades globally (Ault, 2020; Fang et al., 2022; Field et al., 2012; Spinoni et al., 2018; Sreeparvathy & Srinivas, 2022). This is part of a phenomenon called hydrological intensification, whereby global heating is expected to translate into increased variability globally at a range of timescales, and posing serious challenges to water management (Ficklin et al., 2022).

Hydropower generation is closely linked to hydrological conditions in a watershed, and it is sensitive to both seasonal water availability variations (Schaeffer et al., 2012; Teotónio et al., 2017) and to droughts (Van Vliet et al., 2016). This is why climate change, and its widespread projected increases in dry conditions frequency and magnitude, is expected to influence the availability and stability of hydropower generation (Wasti et al., 2022). This challenges the transition to low-carbon energy generation that is necessary to avert climate catastrophe, because hydropower is a mature and reliable technology whose operation produces a renewable and largely emission-free source of energy (Hertwich et al., 2016; Paish, 2002), and it is currently responsible for around 15% of global electricity generation (IEA, 2022). We are in the middle of a hydropower construction boom (Zarfl et al., 2015) with thousands of TWh/year of untapped potential (Gernaat et al., 2017), it is expected to keep playing a role in the global electricity supply in decades to come (Moran et al., 2018; Pokhrel et al., 2018; Winemiller et al., 2016). Hydropower plants are also ideal as a flexible complement to more variable and intermittent power sources such as solar or wind (X. Wang et al., 2019), so increased drought impacts could pose challenges to grid stability in many regions (Jurasz et al., 2018), further hindering the energy transition.

Longer drought periods and hydrological intensification are not only expected to affect the amount of water available to hydropower, but also the efficiency at which water flows can be converted into kinetic energy by

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turbines. Indeed, hydropower turbines are designed based on specific head and discharge characteristics, leading deviations from these conditions to reduce plants' overall operational efficiency (Diaz et al., 2010). In some cases, efficiency can decrease to a point where turbines can no longer work. For instance, the threat of hydropower failure looms large in the Colorado River basin as large reservoirs get depleted (J. Wang & Rosenberg, 2023). In spite of these high-profile cases underlining the urgency of accounting for variable turbine efficiency when designing hydropower plants in a changing climate, there is a gap in research and engineering know-how on this topic. Variable turbine efficiencies are routinely accounted for in studies aiming to increase overall operational performance of an existing plant while meeting several technical, physical, and strategic constraints (Siu et al., 2001; Li et al., 2013; Taktak & D'Ambrosio, 2017; Séguin et al., 2017; Cheng et al., 2021). Yet, time-invariant turbine efficiencies remain the norm during the planning phase, including in recent research evaluating the ability of planned hydropower infrastructure to withstand various climatic and socio-economic stressors (e.g., Bertoni et al., 2019; Bertoni et al., 2021; Hurford et al., 2020; Ray et al., 2018; Taner et al., 2017). This ability to withstand deviations from design conditions is called robustness (Herman et al., 2015), and it is an important element of future-proof planning. Several analytical frameworks have been proposed to evaluate and foster robustness in water systems (Brown et al., 2012; Bryant & Lempert, 2010; Haasnoot et al., 2013; Kasprzyk et al., 2013; Lempert, 2002). They are meant to resolve design and operational problems in conditions where uncertainty is so pervasive that it becomes challenging to form a consensus on how to even represent and tackle it (Kwakkel et al., 2016), a situation known as deep uncertainty.

This paper is the first study to address this gap by proposing an approach to integrate variable-efficiency turbine design into a decision making under deep uncertainty (DMDU) framework that both optimizes hydropower plant design and tests its financial viability under a range of climatic and socio-economic conditions. It focuses on run-of-river (RoR) hydropower plants where turbine system costs are about half of a plant's construction costs (IEA, 2021; Mamo et al., 2018). This cost distribution makes RoR plants an ideal entry point to exploring the interactions between climate change and detailed plant and turbine design. Our approach relies on, and further develops, a state-of-the-art toolbox for run-of-river hydropower design (Yildiz & Vrugt, 2019). It integrates HYPER into a multi-objective robust decision making framework (MORDM; Kasprzyk et al., 2013) to define and evaluate a plant design's financial robustness. The rest of this section provides a detailed overview to small hydropower, including the shortcomings of current planning practices.

Small hydropower plants (SHPs) are generally defined as having an installed capacity of less than 10 MW (Manzano-Agugliaro et al., 2017; UNIDO, 2022), corresponding to an annual production potential under 87.6 GWh. They are a comparably environmentally friendly and less costly alternative to conventional dam-based plants (Tsuanyo et al., 2023). Only 36% of the global potential of small hydropower (≤10 MW) is currently exploited, leaving a substantial untapped capacity of 140 GW (UNIDO, 2022). As a result, a considerable growth of SHP is expected worldwide (Couto & Olden, 2018), including in industrial countries where the best sites for large-scale hydropower are already taken. This is the case for instance in Europe as more public subsidies become available for retrofitting or developing these plants (Kishore et al., 2021; Kuriqi et al., 2020). SHPs provide the option of decentralized power production and sustainable industrial expansion (Hennig & Harlan, 2018) in many areas, including locations that were considered marginal for hydropower production until recently (Hoes et al., 2017; Kosnik, 2010). This study focuses on run-of-river plants (RoR), the most common type of small hydropower plants (Yildiz & Vrugt, 2019). They are characterized by a negligible (sub-daily) storage capacity and by generation almost completely dependent on the quantity and variability of river flows. RoRs accounts for more than 75% of the 3,000 sites (installed capacity over 1 MW) concerned by the current hydropower boom at total (Bejarano et al., 2019; Zarfl et al., 2015). These plants have an important role to play in achieving the seventh SDG goal (Dorber et al., 2020), of ensuring access to affordable, reliable, sustainable, and modern energy for all (McCollum et al., 2017), and in contributing to the achievement of other SDG goals (Gielen et al., 2019).

Yet, ultimately, decisions of whether to build a RoR hydropower plant often depends on its forecast financial viability, calculated with metrics that combine capital costs, operation and maintenance costs, and other relevant measurements (Klein & Fox, 2022). The most common metric to assess is the net present value (NPV), the cumulative sum of all discounted lifecycle cash inflows generated by the power plant (e.g., Bøckman et al., 2008; Hosseini et al., 2005; Santolin et al., 2011; Yildiz & Vrugt, 2019). A project is considered feasible with a positive NPV, and a higher NPV signifies a more favorable outlook. Yet, with its focus on expected profit, NPV is best complemented by metrics that can quantify project risk, such as the internal rate of return (IRR; e.g., Kaldellis et al., 2005; Basso & Botter, 2012), the benefit cost ratio (BC) (e.g., Anagnostopoulos & Papantonis, 2007;

Forouzbakhsh et al., 2007; Nedaei & Walsh, 2022) and the levelized cost of electricity (LCOE; e.g., Zhang et al., 2012; Ceran et al., 2020). Whereas maximizing the NPV leads to a design that offers the highest return, optimizing based on a risk-based metric would result in design with lower risk and investment costs. Despite recognition that there is a trade-off between financial viability metrics for RoR plant design (Basso & Botter, 2012), there remains opportunities for systematic approaches to exploring these possible trade-offs, especially in the context of climate change. In the rest of this work, we choose BC as a metric because of its preponderance in the RoR literature (Klein & Fox, 2022; USBR, 2011). BC is the ratio of discounted lifecycle benefits to the discounted lifecycle costs; maximizing it often results in alternatives that keep costs and risks low (e.g., Anagnostopoulos & Papantonis, 2007; Forouzbakhsh et al., 2007; Nedaei & Walsh, 2022). A value greater than 1 is needed for a project to be deemed feasible, with a higher BC indicating a more favorable scenario, and a lower risk of insolvency. Despite literature cautioning that BC can be easily manipulated in multi-objective cases, where the conversion of a non-monetary objective (e.g., reliability or vulnerability) into a benefit or cost will arbitrarily impact the benefit cost ratio (Lund, 1992), these concerns are not relevant in the majority of RoR plant feasibility studies, as other water uses are treated as constraints that the design will need to meet, rather than given a monetary value.

Research in turbine system design for RoR power plants has received attention recently—recall that the turbine system's cost is on average around 50% of the investment cost of a RoR power plants (IEA, 2021; IRENA, 2012; Mamo et al., 2018). This research is much needed in an area where determining a plant's installed capacity and optimizing turbine system design are still often considered as separate steps performed in this order (DSI, 2012). Yet, turbine system design still rarely considers variable turbine efficiency during plant design optimization (e.g., Kaldellis et al., 2005; Lazzaro & Botter, 2015; Voros et al., 2000). This is despite the fact the operational efficiency of the turbine(s) is crucial to linking flow variability with actual hydropower production (Okot, 2013), and therefore to determining the turbine system best suited for a particular site and river flow characteristics (Yildiz & Vrugt, 2019). Design studies also generally assume that the number of turbines considered is limited to two despite evidence that the use of more than one turbine improves considerably the ability of a RoR plant to respond effectively to seasonal discharge variations (Anagnostopoulos & Papantonis, 2007; Yildiz & Vrugt, 2019). Besides, when the design consists of two turbines or more, they are often assumed to be identical (Amougou et al., 2022; Kaldellis et al., 2005; Mamo et al., 2018),at the expense of added operational flexibility. The HYPER toolbox (Yildiz & Vrugt, 2019) partially addresses these limitations, as it considers variable turbine efficiency and enables to design two-turbine systems with non-identical turbines of a user-specified type—Kaplan, Pelton or Francis. Yet, our understanding on how various climatic but also socio-economic uncertainties—such as interest rates, project cost overruns or energy prices—affect turbine design remains limited, warranting a revisiting to the design of these systems.

The remainder of this study is organized as follows. Section 2 introduces the five case-study sites located in a range of hydro-climatic regions of Türkiye. In Section 3, we discuss traditional RoR hydropower design, cost and benefit analysis. This is followed in Section 4, where we explain the fundamentals of the methodology, including alternatives generation, sampling plausible futures, quantification of robustness and vulnerability analysis. In Section 5 we demonstrate the analysis of the proposed approach with illustrative case studies. The penultimate section of this paper (Section 6) discusses how to have the wider implications of our results and opportunities for future research. Finally, Section 7 concludes this paper with a summary of our main findings.

2. Study Sites

The framework developed in this paper will be applied to five proposed RoR hydropower plants in Türkiye. The map displayed in the top panel of Figure 1 shows they are set in a range of hydro-climatic regions, according to the Köppen-Geiger climate classification derived from an ensemble of four high-resolution climatic maps for the period of 1980–2016 (Beck et al., 2018). This is confirmed by the fact that they exhibit markedly different daily flow duration curves (FDCs; bottom panel of Figure 1). Besik and Kaplan hydroelectric power plants (HEPPs) have a mediterranean-influenced humid continental climate with snowy winters and warm, dry summers. Buyukdere HEPP has a humid continental climate with very cold, snowy winters and warm, dry summers. Tepe HEPP has a humid subtropical climate with warm and humid summers and wet winters. Karacay HEPP is under Mediterranean climate with wet winters and very hot, humid summers. Most precipitation forms as snow during winters for Besik, Kaplan and Buyukdere hydro sites. Snowpack at these sites act as a natural reservoir, providing water throughout the drier summer months which results in less variability in low-flow ranges when compared to

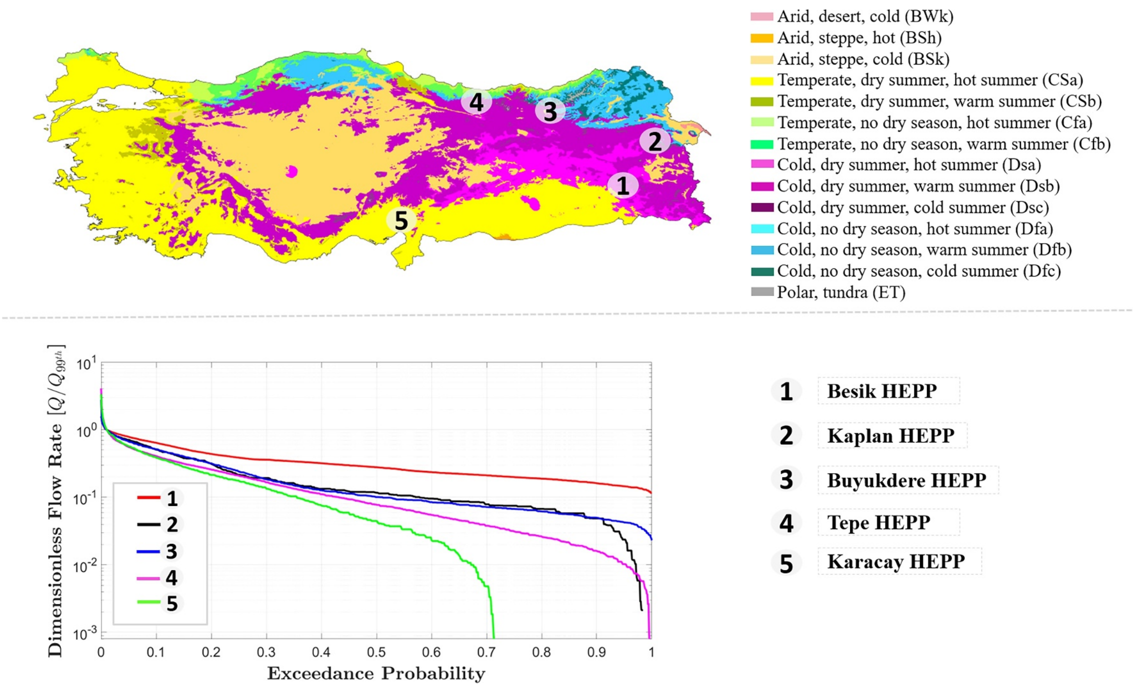

Figure 1. Top panel: Location of the presented five case studies on Köppen-Geiger climate classification map of Türkiye (Beck et al., 2018). Bottom Panel: Presenting Flow Duration Curves (FDC) for five case studies, where normalization is applied based on the 99th percentile of the flow. The FDC depicts graphically the relationship between the magnitude of the discharge (on *y*-axis) and its exceedance probability (on *x*-axis). The flow rate depicted on the *y*-axis is presented using a logarithmic scale.

the other two sites. These catchments' ability to store precipitation characteristically translates into a gentle slope in the middle part of the FDC (Yilmaz et al., 2008), contrary to the Tepe and Karacay sites whose slopes are steeper. What is more, precipitation is rare with short duration in Karacay site, which leads to zero-flow days (green line in bottom panel of Figure 1).

Table 1 summarizes the site and streamflow characteristics of the five different case-studies. Data Availability Statement section provides information on the source of the data used in this study which is obtained from the feasibility reports of DSI. All the sites have sufficient amount of streamflow record with a minimum of 19 years daily discharge data for Tepe HEPP. Drainage areas at all sites are close to each other except Tepe site whose area 405 km^2. The coefficient of variation (CV) is the ratio of the mean by the standard deviation of the daily streamflow time series, and differences reflect the different hydro-climatic regimes in the diverse catchments. As showcased in the bottom panel of Figure 1, where FDC is presented for five case studies with normalization based on the 99th percentile of the flow, variations in precipitation patterns and drainage areas are driving distinct hydrological characteristics. This distinction is also evident in Table 1, indicating a range of 1–6 in mean flows and reveals a threefold difference between the highest and smallest values of CV across the sites. The table also shows the portion of river discharge allocated to minimum environmental flow by state authorities. This quantity

Table 1
Hydrological and Site Characteristics of the RoR Hydropower Plant Case Studies

Case study	Length [Daily]	Drainage area [km^2]	Mean [m^3/s]	Coefficient of variation [−]	Environmental flow [m^3/s]	Gross head [m]	Potential GAAE [GWh]
Besik	27 years	75.1	5.8	0.59	0.63	117	58.31
Buyukdere	36 years	78.7	1.88	1.09	0.156	394	63.65
Tepe	19 years	405	6.22	1.39	0.662	56	29.93
Karacay	34 years	106.2	1.47	1.69	0.18	134	16.92
Kaplan	24 years	100	1.07	1.08	0.12	190	17.47

Note. The data source for this table is provided in Data Availability Statement section.

should be transported by the river network at all times to sustain ecosystem health, and does not go through the turbines. Finally, the table shows the gross hydraulic head available at each site, and the gross potential annual average energy (GAAE) of each site, computed by taking into consideration the available gross head or water pressure, and average long-term discharge. Note that this calculation neglects hydraulic losses, impacts of flow variability on turbine efficiency, and the fact that flows exceeding design plant discharged do not produce hydropower. The different features of these sites will lead to unique hydropower plant designs to best harness available energy. For instance, Besik, Tepe and Buyukdere HEPPs exhibit higher potential compared to other sites, with Besik and Buyukdere having similar hydropower potential. This variation is attributed to significant differences in streamflow and site characteristics, which necessitate distinct hydropower design. Likewise, Karacay and Kaplan HEPPs are located completely different climate zones, yet they have similar hydropower potential despite very distinct site and streamflow characteristics.

3. Run-Of-River Plant Design

First, Section 3.1 explains the key features and assumptions in traditional engineering design of RoR plants. Following this, Section 3.2 details benefit and cost calculations that are key in evaluating project feasibility.

3.1. Traditional Engineering Design

In traditional hydropower plant design, the determination of the design discharge capacity, which is key to determining the installed capacity, is typically addressed separately from the design of the turbine system. The initial step involves determining the design discharge capacity, which is governed by site hydrology and financial constraints. Assuming a long enough record of daily discharge measurements is available, flow duration curves are commonly used to determine this design discharge capacity when over a sufficient period of time are available to construct the curve (Kao, 2013). Figure 2 demonstrates FDC with operating flow boundaries of a typical RoR hydropower plant. The flow rate that is exceeded for 30% of the time (Q_{30}, dashed blue line in Figure 2) is an USBR standard for estimating the optimal installed capacity of hydropower plants (USBR, 2011).

Subsequently, the appropriate type and number turbines are determined based on the chosen design flow and net water head of hydro site. The selection chart shown in left panel of Figure 3 shows three major types of turbines and their manufacturer-recommended ranges for of head and flow (Penche, 1998). Note that available zones overlap, which means that in some cases there is more than one turbine type that is well-suited to the site. The graph is meant to highlight that turbines have technical flow constraints and can only operate effectively within certain flow ranges. The efficiency curve shown for all three turbine types on the right panel of Figure 3 and adapted from Sinagra et al. (2014) further illuminates why different turbine types are best for different sites. The curve introduced illustrates the correlation between the ratio of flow rate to design flow (q/O_d) and efficiency (η). Francis and Pelton turbines are designed for operating with (much) larger heads than Kaplan turbines. Although Francis turbines are highly efficient, they can only operate efficiently over a limited flow range, whereas Pelton turbines maintain a high efficiency even running below design. On the other hand, thanks to its high efficiency at low flows, the Kaplan turbine can be an appropriate alternative to the Francis turbine. The final choice of which turbine(s) to select for a RoR plant warrants a detailed cost benefit analysis along with turbine technical constraints. In most cases, hydropower plants have identical units in the case of more than two turbines installation to make maintenance easier and slightly cheaper (DSI, 2012).

These factors collectively define the operational boundaries of a hydropower plant. For instance, the yellow and magenta shaded areas in Figure 2 represent unexploited hydropower potential due to design limitations and environmental constraints. The Figure highlights that only a portion of the flow can be harnessed as hydropower. Typically, these plants have an average annual capacity factor that falls within the range of 30%–60% (IEA, 2021). Therefore, the expected yearly energy generation of a typical RoR hydropower plant is generally below 60% of its gross potential (GAAE in Table 1 when design capacity is around Q_{30} and capacity factor less than 60%). Factoring in that turbines work have a flow-dependent efficiency, the lack of integration of design discharge determination and turbine system design, coupled with the use of identical turbines, can lead to designs that are inefficient in practice. This can ultimately affect a project's financial feasibility.

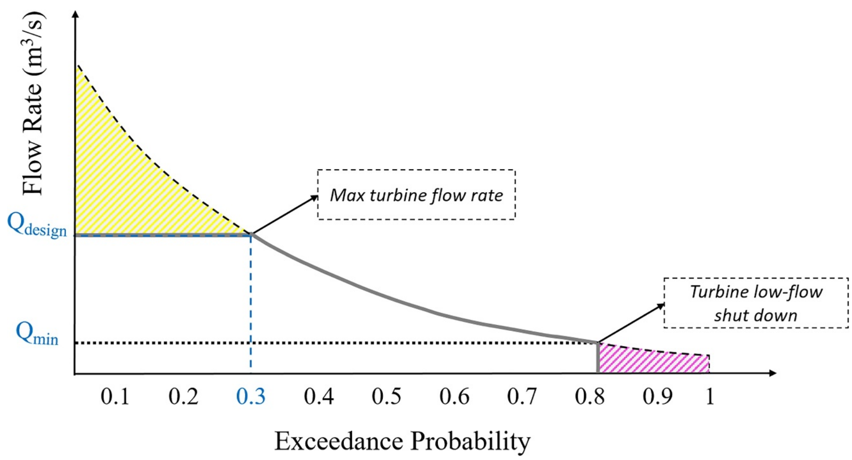

Figure 2. Flow duration curve of the streamflows (dashed black line) and of the flows workable by a RoR hydropower plant (solid gray line). The top yellow dashed area represents the excessive flow that cannot be harnessed by the turbines, while the bottom magenta dashed area represents the flow the plant does not operate due turbine technical constraints and/or ecological flows.

3.2. Benefits and Costs

A comprehensive benefit and cost analysis is crucial to evaluating the feasibility and viability of Run-of-River (RoR) hydropower projects. The main elements of a cost-benefit analysis, detailed in Yildiz and Vrugt (2019) are presented here because they have a key role in the optimization and financial robustness analysis presented in Section 4.

Evaluating the installed capacity of the hydropower project is the first step in the analysis. It also entails assessing the expected generation of energy over the project's lifetime. The installed capacity of a hydropower plant, P is commonly expressed in megawatt (MW):

$$P = \frac{1}{10^3}\,\eta_{\mathrm{g}}\,\rho_{\mathrm{w}}\,g\,H_{\mathrm{net}}(D,O_{\mathrm{d}})\sum_{j=1}^{N} O_{\mathrm{d}j}\eta_j, \tag{1}$$

where the multiplication factor converts the units of P from Watt to kW, η_{g} $(-)$ is the generator efficiency, ρ_{w} (kg/m^3) is the density of water, g (m/s^2) signifies the gravitational constant, H_{net} (m) is the net head or water pressure

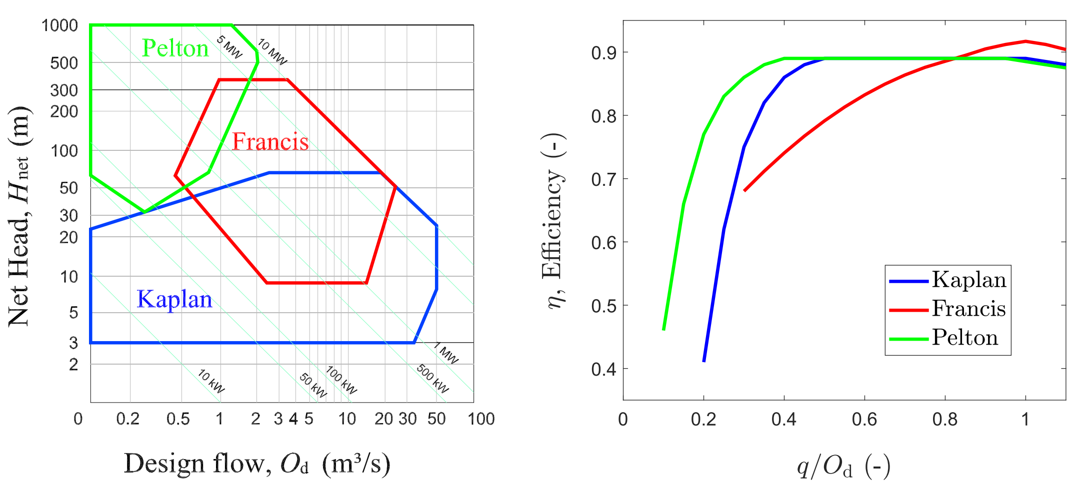

Figure 3. Left panel: Turbine chart (Penche, 1998). Right panel: Efficiency of the Kaplan (blue), Francis (red), and Pelton (green) turbines as function of the ratio between their flow rate and design flow respectively (Sinagra et al., 2014).

at the bottom of the penstock, O_d (m^3/s) signifies the system design flow, D (m) denotes the penstock diameter, O_{dj} (m^3/s) and η_j (−) characterize design flow and efficiency of the jth turbine, respectively.

The amount of energy E that a N-turbine hydropower plant ($N \in 1, 2, 3$) can produce over a time period, Δt (days), is calculated in kilowatt hours (kWh) via:

$$E(t) = 24 \sum_{t}^{t+\Delta t} \sum_{j=1}^{N} P_j(t) \left[q_j(t)\, H_{\text{net}}(t)\, \eta_j(t) \right], \tag{2}$$

where the multiplication factor converts the units of day to hour, t (days) denotes time, P_j is the power produced by the jth turbine, and q_j is the volumetric water flux of the jth turbine, expressed in m^3/s. Note that H_{net} and η_j are time dependent and vary as function of turbine inflow, penstock diameter and/or design flow, respectively.

The expected cumulative revenues from hydropower production through the lifecycle of the project are computed through:

$$\mathrm{R} = \frac{R_1}{1 + r(1)} + \frac{R_2}{(1 + r(2))^2} + \cdots + \frac{R_{L_s}}{(1 + r(L_s))^{L_s}} \tag{3}$$

where L_s is the project's lifetime, typically 50 years, and $\mathbf{R} = \{R_1 \ldots, R_{L_s}\}$ and $\mathbf{r} = \{r(1), \ldots, r(L_s)\}$ are L_s-vectors with the annual plant revenues in US dollars assuming an average hydropower production throughout the year ($) and the annual interest (discount) rate in %, respectively.

The final stage of a cost-benefit analysis involves estimating the total cost of a RoR hydropower plant design, which significantly depends on site-specific factors. Computing total project costs entails the summation of construction costs and maintenance costs. These include yearly maintenance and operation cost on the total cost, but also the need to replace the electro-mechanical equipment at the end of its design life, typically 25 years. Hence, the total net present cost of a project is given by:

$$\mathrm{C} = C_{\text{Tp}} + \frac{C_{\text{om}}}{1 + r} + \frac{C_{\text{om}}}{(1 + r)^2} + \cdots + \frac{C_{\text{om}} + C_{\text{Rem}}}{(1 + r)^{25}} + \cdots + \frac{C_{\text{om}}}{(1 + r)^{L_s}} \tag{4}$$

where, C_{Tp} is the cost of construction, C_{Rem} is the renovation and reconstruction cost of electro-mechanic equipment at year 25 and C_{om} is the yearly maintenance and operation cost.

This study uses and extends HYPER (Yildiz & Vrugt, 2019), a state-of-the-art toolbox that calculate the technical performance, energy production, maintenance and operational costs, and economic profit of a RoR plant in response to a record of river flows and suite of different design and project variables. The HYPER model, along with recent improvements are provided in Supporting Information S1 to this paper.

4. Methodology

In this paper we first explore the impact of using alternative financial objectives for design, then evaluate the financial robustness of design solutions in a changing world. These modeling choices, along with the taxonomy for robustness frameworks introduced by Herman et al. (2015), informed our use of an analysis framework adapted from Many-Objective Robust Decision-Making (MORDM; Kasprzyk et al., 2013), in which we incorporate for the first time turbine design considerations thanks to the improved HYPER toolbox (Section 3). We outline the four main steps of our analysis in Figure 4, each of which is detailed in a separate sub-section.

In step (I), we formulate a set of single- and multi-objective design problems to be solved by coupling of a multi-objective evolutionary algorithm (MOEA) with HYPER and using a statistically robust representation of flow variability (Section 4.1). This is a prerequisite to evaluating the consequences of design assumption on robustness. Step (II) features the sampling of deeply uncertain factors to analyze robustness to uncertain climatic and financial futures, along with careful justifications for the chosen ranges (Section 4.2). In step (III) we define and two quantify financial robustness metrics (Section 4.3), and in step (IV) we discover and analyze the main factors that influence robustness (Section 4.4).

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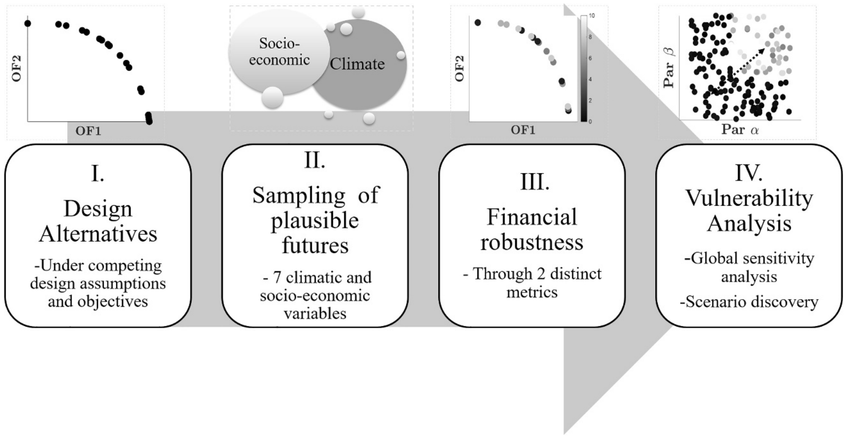

Figure 4. Methodological flowchart of our the design of financially robust RoR hydropower plants. Each step is associated to the sections of the paper in which it is discussed.

4.1. Generation of Design Alternatives

In this section we present the experimental design to explore different financial design objectives. These objectives are evaluated through daily streamflow time series, so the method for daily streamflow generation (Section 4.1.1) is presented before the objective themselves (Section 4.1.2). Then, Section 4.1.3 details the experimental design for RoR optimization.

4.1.1. Synthetic Streamflow Generation

RoR plant performance is evaluated through 20 time series of 50 years of daily streamflows generated by synthetic time series generation. In this study, we used the Kirsch-Nowak streamflow generator for synthetic streamflow generation already used in several existing robustness assessments (Giuliani et al., 2014; Quinn et al., 2018) for its ability to reproduce the statistical characteristics of the historical record. By generating these flows during a longer period of time than the period of record, we also provide a more accurate picture of variability and extremes associated with the historical streamflow regime.

4.1.2. Objective Functions (OFs)

Since we are investigating financial robustness, objectives we consider have to do with the total lifetime expected revenue R and cost C as defined in Equations 3 and 4 respectively. We first define expected total discounted revenue and cost as objectives in their own right:

$$\begin{cases} f_{\text{revenue}} = \mathrm{R} \\ f_{\text{cost}} = \mathrm{C} \end{cases} \tag{5}$$

The most common design objective is the maximization of the net present value (NPV), defined as the value of projected cash flows discounted to the present (Santolin et al., 2011):

$$f_{\text{NPV}} = R - C \tag{6}$$

As discussed in the introduction, there exist alternative metrics to NPV that help to find less risky designs. In this work, we selected the cost-benefit ratio (BC) because it is the most easily interpretable in relation to NPV. BC is defined as present value of net positive cash flow divided by net negative cash flow, and reads:

$$f_{\text{BC}} = \frac{R}{C} \tag{7}$$

Finally, we defined as an objective the worst first percentile annual energy production from our 1,000 years synthetic time series to account for energy production during droughts. This is because incorporating risk-averse objective in multi-objective optimization is a common practice where decision-makers need to make robust and reliable decisions in the face of uncertainty (e.g., Giuliani et al., 2017). This approach is much less sensitive to the time series used than would be using the single worst year (Quinn et al., 2017). Worst first percentile energy production rate is expressed as:

$$f_{\mathrm{dry}} = percentile(E_{\mathrm{a}}(k), 1) \qquad (k = 1, 2, \ldots, K_{\mathrm{s}}), \tag{8}$$

where $E_{\mathrm{a}}(k)$ is equal to the sum of the daily values of $E(t)$ in Equation 2 computed by HYPER for year k, and K_{s}, is the number of flow years used for energy production of the power plant.

4.1.3. Design of Experiments

We consider four design formulations. For all four formulations below the search aims to generate design alternatives. A design consists of turbine configurations (single, dual and triple), turbine type (Francis, Kaplan, Pelton) and related design parameters (penstock diameter, turbine(s) design flow) of the RoR hydropower plant. HYPER is used to simulate all proposed design during the searches, and it is coupled in a simulation-optimization setup with the Amalgam MOEA (Multiobjective Evolutionary Algorithm) introduced by Vrugt and Robinson (2007). Amalgam MOEA is a self-adaptive multi-method search which employs four sub-algorithms simultaneously within its structure, including NSGA-II, adaptive metropolis search, particle swarm optimization and differential evolution (Vrugt & Robinson, 2007). Amalgam MOEA was benchmarked against another state of the art algorithm, Borg MOEA (Hadka & Reed, 2013) as a check of its appropriateness for RoR design optimization (see Supporting Information S1). It can be used both in single- and multi-objective settings. With all four formulations, the search was conducted using a population size of $I = 100$ individuals and running Amalgam for $J = 1000$ generation.

Our first formulation corresponds most closely to a traditional RoR design: identical turbine design (ID) with NPV maximization, with NPV defined in Equation 6. This corresponds most closely to a traditional RoR design. In this case, we have considered two different configurations; (a) ID alternative; identical turbines with the same cost assumptions as other alternatives, (b) ID* alternative; the cost of electromechanical equipment (see Supporting Information S1) is reduced by 10% which is then propagated through Equation 4.

Second, we propose a single-objective NPV maximization where turbines are allowed to be different. This mirrors the previously published iteration of HYPER (Yildiz & Vrugt, 2019). This is our benchmark. In the two multi-objective formulations below, turbines are allowed to be of different design flow and installed capacity as well.

Third, we explore the possible trade-off between NPC and BC as design objectives, with the following two-objective problem:

$$F_3(x) = \max\left[\, f_{\mathrm{NPV}},\ f_{\mathrm{BC}} \right] \tag{9}$$

where x is the vector of decision variables including all the key design parameters. This enables us to compare the robustness of solutions with how they trade-off the most commonly used traditional design objective with another financial objective assumed to be more focused on project risks.

Finally, we present an explicit three-objective formulation where we explicitly use the two components of f_{NPV} and f_{BC}, discounted lifetime revenue and cost, as standalone revenue and cost objectives f_{revenue} and f_{cost}. We add the dry year revenue objective f_{dry} defined in Equation 8 as our third objective, in order to explore possible tradeoff between these two key financial objectives and hydropower revenue during dry periods. This formulation aims to verify that the two-objective search does not ignore obvious financially robust solutions. Formally, this problem is expressed as:

$$F_4(x) = \min\left[-f_{\mathrm{revenue}}, f_{\mathrm{cost}},\ -f_{\mathrm{dry}}\right] \tag{10}$$

Table 2
Variables and Sampling Ranges Used for Robustness Analysis

Uncertain factor	Current value	Lower bound	Upper bound	Comments
r, Interest (discount) rate (−)	0.095	0.03	0.15	Significant variations in applications
e_{Pf}, Energy price, first 10 years (¢/kWh)	5.5	5	6.5	Feed-in tariffs mechanism
e_{Pr}, Energy price, rest of the years (¢/kWh)	5.5	3	6.5	Relatively high variability in market prices
C_{or}, Cost overrun SF (−)	1	1	3	Elevated likelihood of construction delays
$\tilde{m}$, Median SF (−)	1	0.3	1	Expected rise in drought conditions
CV, Coefficient of Variation SF (−)	1	1	2	Expected increased variability in flow
$P_{1\mathrm{st}}$, 1st percentile SF (−)	1	0.3	1	Expected rise in drought conditions

Note. SF is for scaling factor, and a SF of 1 indicates baseline conditions.

4.2. Sampling Plausible Futures

The second element of the approach described in Figure 4 is to evaluate the performance of the alternatives identified under competing design assumptions across a set of uncertain future states of the world (SOWs). This is a commonly employed strategy in methodologies that explore the robustness of water systems in situations where quantifying uncertainty remains challenging (e.g., Herman et al., 2015; Ray et al., 2018). For this, we first assigned a range to multipliers for each of these seven variables (Table 2).

The four socio-economic variables in Table 2 are as follows. The interest rate, r, used to asses the net benefits of projects have varied widely. Therefore, A range of 3%–15% is considered to explore the impact of r on financial viability of a plant. The two electricity prices reflect Türkiye's economic regulations. A first price e_{Pf} is fixed for the first 10 years by the Turkish government, including subsidies (EMRA, 2022), with a different energy price for the remainder of the project's lifetime e_{Pr} with less protection against lower prices. Costs overruns resulting from construction delays double average construction costs, with significant project-to-project variability (Ansar et al., 2014; Callegari et al., 2018), leading to the range for the cost overruns scaling factor C_{or}.

The 3 hydroclimatic parameters are streamflow statistics: its median, $\tilde{m}$, coefficient of variation, CV, and first percentile, $P_{1\mathrm{st}}$. The ranges considered in Table 2 reflect the expected impacts of climate change toward drying and higher variability (see detailed explanations in the Supporting Information S1). These ranges are then converted into flow duration curves (FDCs) using a novel approach (Yildiz et al., 2023). In this approach, streamflow statistics that are of interest to water resource management; median, standard deviation and first percentile flows are related to the three parameters of a statistical representation of the FDC. New FDCs are then generated to represent full flow distributions that mirror these parameters, and they can be used in our subsequent robustness analysis. Panel A of Figure 5 demonstrates how the FDC samples our methods provides differ from the baseline and the wide range of flow conditions considered. Clearly, our method can match the expected drying and

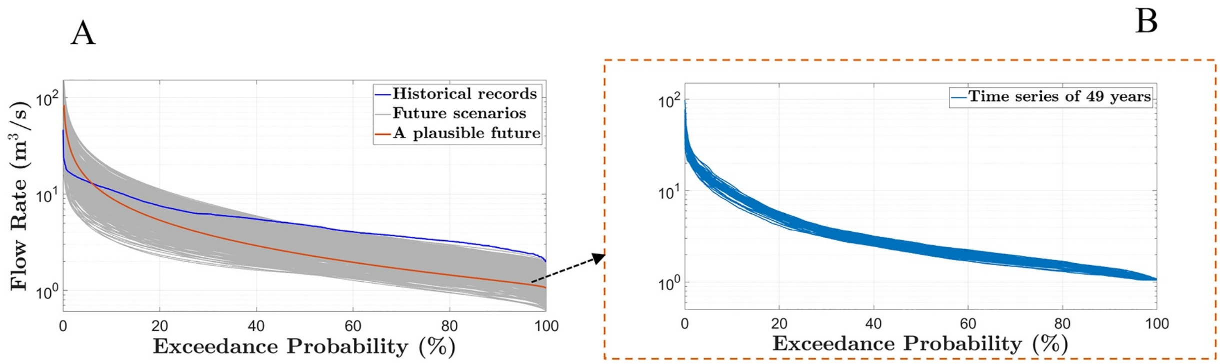

Figure 5. Plot of the flow duration curves (FDC) of the fitted Kosugi model (blue line) and sampled flow duration curves (gray lines) and a moderately dry future (orange color) constructed by deriving the FDC parameters for Kosugi Model shown in Table 2 (panel A). Disaggregation of a moderately dry future (orange color) to 50 time series of 49 years (panel B). The flow rate displayed on the y-axis is presented on a logarithmic scale.

increased variability expected in the region as the result of climate change in the region. Each sampled FDC consists of 50 time series of 49 years daily discharge values which are created by combining the statistical generation of climate-perturbed FDCs with the Kirsch-Nowak streamflow generator. Decomposition of a fairly arid future (orange color) into 50 time series of 49 years is shown in panel B of Figure 5.

Note that multiplier ranges in Table 2 represent plausible rather than probable values. They provide a mechanism for understanding how wrong our baseline model assumptions can be before significant vulnerabilities to deep uncertainties occur (Herman et al., 2014). After determining ranges for the variables, we constructed a 7-dimensional Latin Hypercube Sample of 500 future states of the world (SOWs) to reflect the deep uncertainties across socio-economic and hydroclimatic futures. After preliminary results showed the key role of the cost overruns scaling factor, our final sampling uses Progressive Latin Hypercube Sampling strategy introduced by Sheikholeslami and Razavi (2017) so cost overruns scaling factors sampled in the 1–2 and 2–3 ranges are both a latin hypercube sampling with 250 future SOWs. A comprehensive justification for all these parameters and their associated sampling ranges can be found in detail in Supporting Information S1.

4.3. Metrics for Financial Robustness

The third element of our approach in Figure 4 is to evaluate financial robustness of selected (or all) alternatives across a set of uncertain states of the world, using two distinct but complementary financial feasibility metrics. Using more than one robustness metrics makes conclusion more solid because metric choices usually affect our evaluation of the robustness of competing options (Giuliani & Castelletti, 2016; Herman et al., 2015; McPhail et al., 2018). Note that this step takes place after the generation of design alternatives (see Section 4.1), so the turbine setup remains unchanged throughout each design alternative's operational lifetime and across all plausible future scenarios analyzed.

4.3.1. Two Financial Feasibility Metrics

The payback period (PB) is a metric that shows the length of time required to recover capital investments. It is computed as;

$$PB = \frac{C_{Tp}}{\overline{R} - C_{om}} \tag{11}$$

where C_{Tp} it the investment cost defined in Equation 4, and the denominator is the expected amount of net cash inflow that the project generates each year. The desirability of an investment of high initial cost such as hydropower plants is directly related to its PB (Lin, 2010). A shorter PB indicates a high net cash flow compared with the initial investment, and therefore a project that will pay for itself (and repay annual installments on any loan) more easily. In addition to its simplicity, the PB formula also serves as a straightforward risk analysis tool (Yard, 2000).

Yet, PB does not account for the long-term profitability of the investment since it ignores any returns generated beyond the payback period (Lefley, 1996). Besides, it does not take the time value of money into account. To account for these we also complement PB with NPV to asses robustness. Whereas PB evaluates the attractiveness of an investment in absolute terms, NPV assesses the relative value of investing versus not investing.

4.3.2. Robustness Metric Construction

The payback period (PB) which is a metric that shows the length of time required to recover capital investments and NPV are transformed into robustness metrics based on satisficing criteria (Herman et al., 2015) that is, by comparing these values to a desirability threshold.

In general, small hydropower projects are considered feasible if the PB is less than 15 years (Ak et al., 2017; Alonso-Tristán et al., 2011; Girma, 2016). Therefore, for each of the 49-year time series we define robustness based on PB as a binary variable:

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$$\mathrm{RM}_k = \begin{cases} 0, & \mathrm{PB} > 15 \text{ years} \\ 1, & \mathrm{PB} \le 15 \text{ years} \end{cases}$$

These binary variables are aggregated over all 50 time series for each plausible future to form an average robustness score RM_{PB} over all 500 futures—or less excluding the futures where the flow median is lower than or close to the first percentile. For each of the plausible futures, we also assigned success if at least 75% of the time series (38 of 50 or more) verify $RM_k = 1$.

We calculate the robustness metric based on NPV, RM_{NPV}, using the same approach as RM_{PB}. For each of the 49-year time series we define robustness as a binary variable:

$$\mathrm{RM}_k = \begin{cases} 0, & \mathrm{NPV} > 0\ \$ \\ 1, & \mathrm{NPV} \le 0\ \$ \end{cases}$$

Then, we aggregate over all 50 time series over all futures to compute RM_{NPV}. Alternatively, we define a future as success or failure depending on whether $NPV > 0$ over 75% of the time.

4.4. Vulnerability Analysis

Finally, we carry out a vulnerability analysis in two steps. First, a global sensitivity analysis (Saltelli et al., 2008; Sobol, 2001) of robustness metrics through the method of Sobol' will aim to find the uncertainties financial robustness is most sensitive to. We then use scenario discovery to understand what combinations of uncertainties might lead to critical system failures. We then conducted scenario discovery analysis to identify the thresholds of deeply uncertain factors responsible for critical system failures by using a logistic regression method to separate success regions from failure regions. The model evaluations were performed using the ShARC high-performance cluster (HPC) at the University of Sheffield.

5. Results

In this section, we first illustrate analysis results using the case of the Besik hydropower project, which is expected to be the most profitable based on conventional assessments of RoR plants. We start by presenting design alternatives determined by various sets of objective functions, and by quantifying their robustness across the plausible futures we sampled (Section 5.1). We then investigate how the deeply uncertain hydrologic and economic factors affect the performance of these alternatives (Section 5.2). The result of this analysis is then compared with the other four case studies in Section 5.3.

5.1. Single-Site Design Optimization and Robustness

Results of the four competing design optimizations introduced in Section 4.1 are presented for the Besik site in Figure 6 in the space of design objectives NPV (x-axis) and BC (y-axis). Recall that in this work, design optimization uses historical flows. f_{NPV} denotes single-objective NPV optimization, F_3 involves two objectives—NPV and BC optimization, and F_4 represents the three objectives of revenue, cost, and dry year revenue optimization. Identical turbine solutions (ID) are identified through a single-objective NPV optimization. We differentiate between raw solution results (ID solution), with the same design for which a 10% discount is applied to the cost of electro-mechanical equipment and propagated through Equation 4 (ID* solution). This latter solution is used to check the solidity of our results under the possibility that turbine manufacturers may be able to lower the cost of electromechanical equipment when turbines are identical. The Francis and Pelton turbines are the most suitable options for this project. The efficiency of Francis turbines makes them a superior choice over Pelton turbines to reflect the relative lack of streamflow variability at this site. This is because Francis turbines are highly efficient under steady or moderate flow conditions. Besides, while the F_3 formulation only includes a configuration with dual Francis turbines, the F_4 formulation offers a wider range of alternatives including a single Pelton turbine, a single Francis turbine, dual Pelton and dual Francis designs, and even a triple Francis turbine configuration to satisfy different objectives. Indeed, triple Francis operations have the highest energy revenue with the largest design parameters (e.g., discharge design capacity, penstock diameter). Yet, these designs are costly, so the NPV is low when compared to dual configurations. The left panel compares the F_3- and F_4

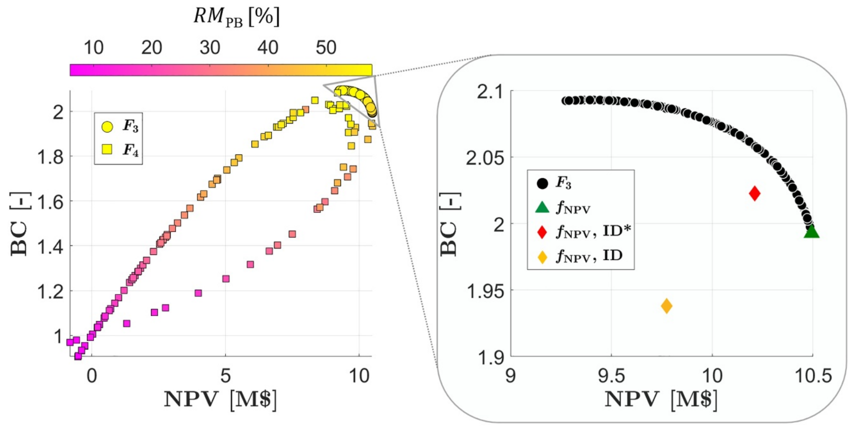

Figure 6. Left panel: two-dimensional NPV and BC objective space where the alternatives of F_3 formulation (circles) are compared against the F_4 formulation (squares). Each solution colored by its robustness measure, $\mathrm{RM}_{\mathrm{PB}}$. Right panel: the alternatives of the F_3 formulation (black circles) and identical turbine solution (orange diamond) and identical turbine solution with discount (red diamond) and best NPV solution (green triangle) based on single NPV optimization.

formulations, and each alternative is also colored by its robustness measure, RM_{PB}, value. This enables us to verify that despite the presence of a dry-year production objective in the F_4 formulation, it does not find more robust solutions than the design alternatives found in the F_3 formulation. The F_4 optimization also offers many solutions that are far from the more profitable region in terms of costs and benefits. For these reasons, alternatives from the F_4 formulation will not be analyzed further, and we will focus on comparing results from the F_3 with "traditional" designs using NPV as a single objective, with or without identical turbines. The right panel zooms in on the region of the NPV-BC space where the solutions from these f_{NPV} and F_3 formulations are all present, including the best NPV solution with different-size turbines (green triangle), as well as identical turbine solutions (red and orange diamonds).

All designs found across these three competing optimization formulations consist of two Francis turbines. The absence of three-turbine solutions demonstrate that the dual Francis option is sufficient to operate in the historical flow range for the site. Each line in the parallel plot of Figure 7 represents a design alternative with (a) its design

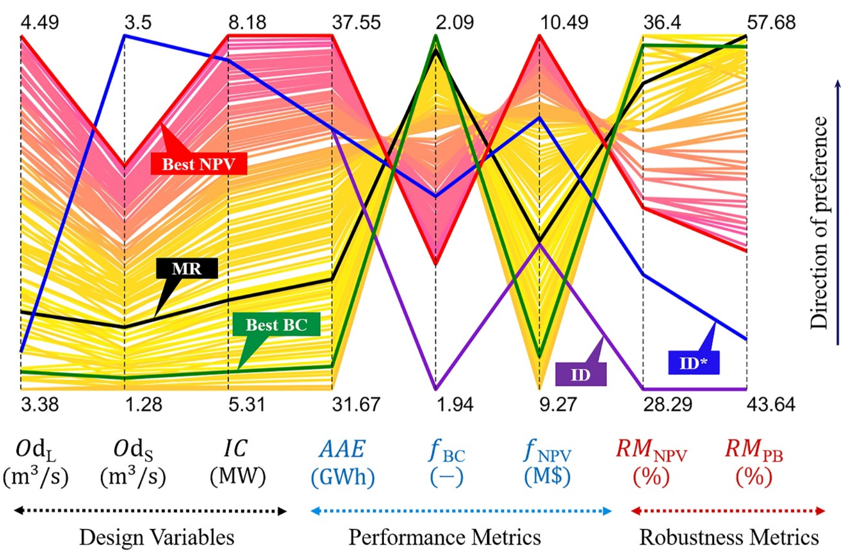

Figure 7. The parallel plot of (1) design parameters of alternatives:large turbine design flow, O_{dS} (m^3/s), small turbine design flow O_{dL} (m^3/s), installed capacity IC (MW), average annual energy AAE (GWh), (2) two objective functions: f_{BC} (−), f_{NPV} (M$), and (3) their respective robustness measures value $\mathrm{RM}_{\mathrm{NPV}}$, $\mathrm{RM}_{\mathrm{PB}}$ (%). Color coding in lines is used for classification of results based on $\mathrm{RM}_{\mathrm{PB}}$ value.

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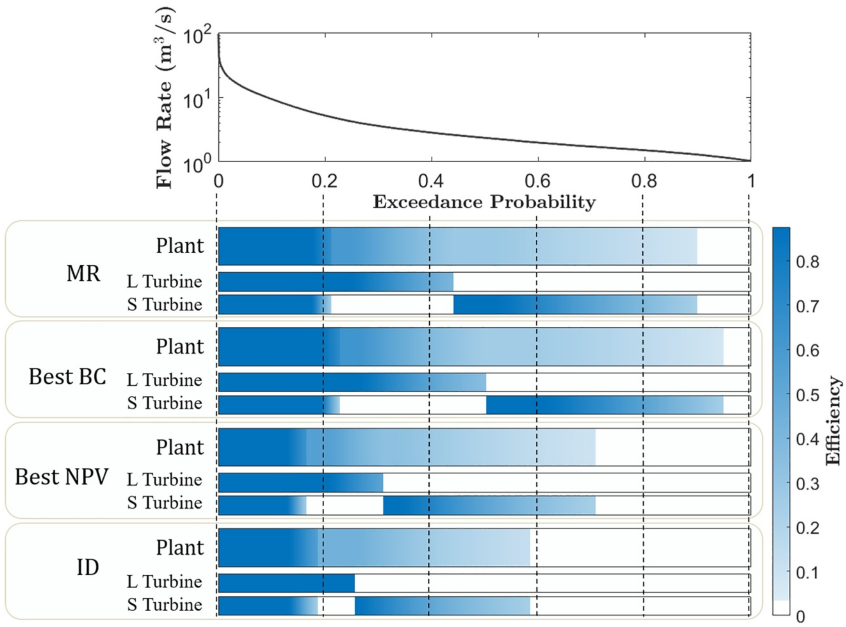

Figure 8. Operational plant efficiency (labeled as plant) and turbine efficiencies (Large turbine and Small turbine) of each selected alternatives under a the future highlighted with the orange line in Figure 5. Recall that the ID and ID* designs are identical. The vertical dashed lines represent the scale of probabilities.

parameters: design flows of the large and small turbine, installed capacity, average annual energy production, (b) the values of the BC and NPV design objectives (regardless of whether BC was used as an objective in design determinations), and (c) the two financial robustness measures introduced in Section 4.3. Across the alternatives, we highlighted a few remarkable solutions, noted MR (most robust based on RM_{PB}), best NPV (based on single objective NPV optimization), the best BC solution from the two-objective optimization, ID and ID* (identical turbines NPV maximization). The color of each line represents RM_{PB}, the average probability of timely payback across all futures. It is apparent that RM_{PB} correlates favorably with f_{BC} and smaller design alternatives with less turbines design discharge and installed capacity. It additionally exhibits a negative correlation with f_{NPV} and annual energy capacity due to the fact that greater generation capacity necessitates a larger, and thus more expensive, design. The two robustness measures clearly provide comparable evaluations of alternative designs. When contrasting robustness of a design with its NPV, designs with the highest NPVs show less robustness to both climate change (and associated drying) and to evolving financial conditions than smaller design alternatives with less installed capacity. Interestingly, RM_{NPV} is also lower for the best NPV alternative than for solutions with smaller NPV but higher cost-benefit ratio. Besides, the best BC and MR alternatives have comparable design characteristics and superior f_{BC} values that contribute to being robust to uncertain futures. On the other hand, robustness of identical turbine alternative (ID) even with less expensive design (ID) noticeably lower than all of the two objective alternatives.

To further analyze why designs with smaller installed capacity and turbine design flows seem to be more financially robust across a set of plausible futures featuring drier and more variable conditions, we display in Figure 8 the operational performance of each selected alternative from Figure 7 under a moderately dry future (top panel) which is also highlighted (orange color) in Figure 5. For each alternative (recall that ID and ID* are identical designs), the top, thicker horizontal bar represents overall plant efficiency whereas the thinner bars display the respective efficiencies of the large and small turbines. Both MR and Best BC alternatives have similar performance and they generate energy most of the time. Whereas the larger turbine of both MR and Best BC alternatives can only operate up to 50% of the time, the small turbine is able to function and retain high efficiency even with low flows. In contrast, plant efficiency of the best NPV design is lower than 0.3 most of the time (60%) and it has to be shut down almost a third of the time. What is more, the large turbine of best NPV alternative shuts down more than three quarters of the time. Since it is even less flexible than the best NPV alternative, the ID alternative has the longest period without operation (about 40% of the time) and the lowest overall capacity factor

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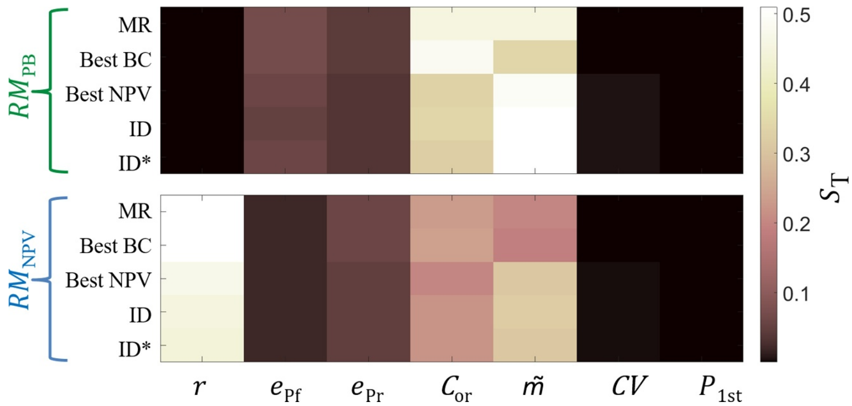

Figure 9. The effect of the uncertain factors (x-axis) is quantified with the total-order S_{T}, sensitivity index (y-axis) based on robustness metric, $\mathrm{RM}_{\mathrm{PB}}$ (first row) and $\mathrm{RM}_{\mathrm{NPV}}$ (second row) and where dark gray is insensitive and white is sensitive.

among the selected alternatives. Note that the selected future (see orange line in Figure 5) does not represent a very dry future. It is clear that the operational performance of a smaller, more flexible design with a higher benefit-to-cost ratio (BC) will be much better than that of a more traditional design under futures where we could observe increased frequencies of both high flows and low flows.

5.2. Single-Site Vulnerability Analysis

In this section, we analyze how the deeply uncertain hydrologic and economic factors influence the performance of the five alternatives highlighted in Figures 7 and 8. First, we compute the Sobol' global sensitivity indices, with the total-order sensitivity S_{T} shown in Figure 9. This sensitivity metric accounts for the total contribution of each factor to the variance of each robustness metric—both by itself and in interaction with other factors (Saltelli et al., 2010). When the robustness metric is RM_{PB} (top panel on Figure 9), the most sensitive factors are the cost overrun C_{or} and median streamflow $\tilde{m}$ scaling factors, and this is true for all the selected alternatives. Note their relative importance changes: the NPV-maximization designs (NPV, ID and ID*) are more sensitive to decreasing median flows because they are less flexible designs aimed at capturing high-flow conditions better. Conversely, cost overruns are key to the payback in smaller, more flexible designs BC and MR. Since interest rates do not enter in payback calculations (see Section 4.3, this metric is insensitive to changes in r). Contrary to this, Sobol' identifies the most sensitive factor as the interest rate for all the selected alternatives when the robustness metric is RM_{NPV} (bottom panel on Figure 9). This sensitivity to the interest rate is not surprising given the definition of NPV, but the difference between the two financial robustness metrics is striking given the fact that they provide similar rankings of alternatives (see Figure 7). However, similar to RM_{PB}, RM_{NPV} is also sensitive to C_{or} and $\tilde{m}$, with similar relative importances of these two factors across designs. The impact of energy price is insignificant for both financial robustness metrics as the range of energy price, especially for the first 10 years, is well defined that has a narrower range than any other factors. Similarly, both of the robustness metrics are insensitive to flow variability, CV, and low flows, $P_{1\mathrm{st}}$, confirming that both high and low flows are less influential to RoR energy production when compared to the central tendency. Moving on to scenario discovery, Figure 10 assesses where, in the space of uncertain factors, the solution labeled MR solution (most robust for RM_{PB}) fails to meet the performance requirements for each financial robustness metrics. Each panel plot contains a pair of two-dimensional projections of the 7-dimensional uncertainty space, with each point representing one of the 456 distinct feasible SOWs. A logistic regression model is then fitted to estimate the probability of failure as a function of selected two parameters to define success and failure regions. Not surprisingly, wetter worlds (higher median) decrease the probability of failure for both metrics. Clearly, any increase in cost overrun and decrease in median and energy price results in movement to the failure region, indicating high sensitivity of even the most robust solution to each of these factors when robustness metric is RM_{PB}. If a decrease in cost overrun is accompanied by increases in the energy price, the MR solution can tolerate greater decreases in the flow conditions. On the other hand, when the robustness metric is RM_{NPV}, any increase in interest rate and cost overrun and decrease in median and energy price results in movement toward the failure region, confirming high sensitivity of even the most

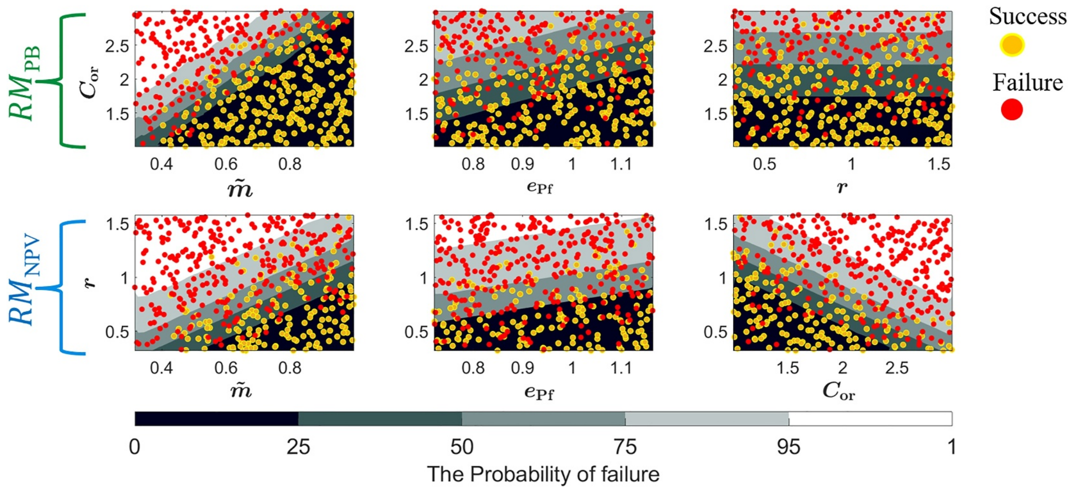

Figure 10. SOWs in which the MR solution fails to meet the defined performance requirement in the two dimensional projection defined by the scaling factors on each uncertain factor. Panel plots at the first row shows analysis results of RM_{PB} and second row shows for RM_{NPV}. Yellow points indicate states of the world where the MR solution satisfy to meet the performance criteria, and red points indicate states of the world where solution fails. The probability of failure as a function of these three factors is also shaded for each panel.

robust solution to each of these factors. The MR solution can tolerate greater increases in the interest rate, and the energy price for if the wetter worlds are accompanied by decreases in cost overrun. Figure 10 emphasizes the importance of considering multiple uncertainties in combination.

To further visualize which climatic futures foster success or failures for different alternatives, in Figure 11, we plotted future FDCs (thin gray lines) and highlighted specific successful (orange lines) FDCs where the highest BC alternative meets the RM_{PB} robustness threshold, that is, has 75% chance of having a payback period under 15 years, whereas another solution does not (left panel: NPV maximization solution; right panel: ID solution). The best BC alternative is robust in 39 additional SOWs (11.7%) compared to the best NPV design, and in 62 additional SOWs compared to the ID design. It is clear that Best BC alternative can tolerate greater decreases in future streamflow values than best NPV and ID alternatives. What is more, identical turbine configuration is significantly more vulnerable to climate change due to a lower flexibility across the range of plausible flows. Dependent on socio-economic factors, it can even fail with a FDC at the higher end of the range.

5.3. Comparison of All Cases

This section gives the results of the analysis across all study sites listed in Section 2. The design characteristics, financial and energy performance metrics and the financial robustness metrics for the same five alternatives as in

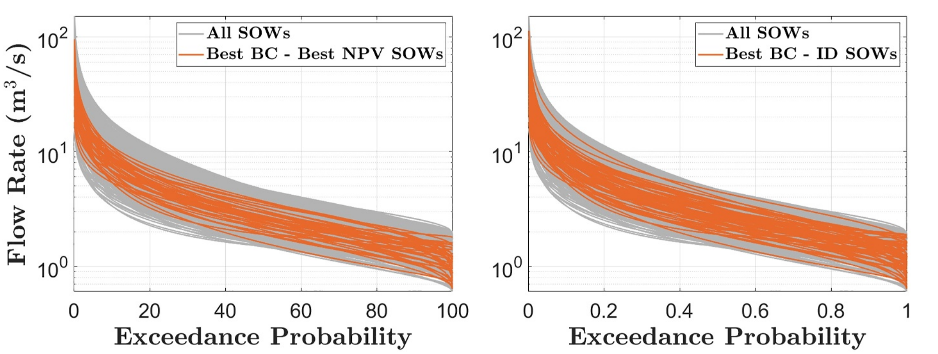

Figure 11. The plots of FDC in which the highest BC alternative meet the performance criteria whereas the highest NPV alternative fails(left panel), and the ID alternative fails (right panel). Orange colored lines shows successful SOWs, gray lines represents all the SOWs.The flow rate displayed on the *y*-axis is presented on a logarithmic scale.

Table 3
Design Characteristics, Performance Metrics and Robustness of the Most Robust (MR) Alternative and the Alternative With Highest NPV and BC, Identical Turbine Alternatives (ID, ID) of Given Five Case Studies*

Case study alternatives	Turbine configuration	IC [MW]	AAE [GWh]	f_{NPV} [M$]	f_{BC} [−]	RM_{PB} [%]	RM_{PB} $C_{or} < 2$ [%]	RM_{NPV} [%]	RM_{NPV} $C_{or} < 2$ and $r < 1$ [%]
Besik, MR	Dual Francis	6.03	33.5	9.78	2.08	57.6	79.7	35.3	76.2
Besik, BC	Dual Francis	5.45	32.05	9.38	2.09	57.2	81.5	36.1	80.3
Besik, NPV	Dual Francis	8.18	37.55	10.49	1.99	49.1	68.7	32.4	70.4
Besik, ID	Dual Francis	7.98	36.01	9.77	1.92	43.6	62.9	28.2	64.7
Besik, ID*	Dual Francis	7.98	36.01	10.21	2.02	45.6	64.3	30.9	69.6
Buyukdere, MR	Dual Pelton	7.49	29.65	8.33	2	65.8	86.8	41.2	83.8
Buyukdere, BC	Dual Pelton	5.22	24.41	7.11	2.08	61.8	86.8	39.4	84.5
Buyukdere, NPV	Dual Pelton	9.96	34.10	8.81	1.85	63	83.6	39.4	80.8
Buyukdere, ID	Dual Pelton	9.43	32.81	8.51	1.86	60.2	82	37.4	79.4
Buyukdere, ID*	Dual Pelton	9.43	32.81	8.90	1.93	62.6	82.8	40.2	81.6
Tepe, MR	Triple Francis	3.78	14.75	3.09	1.60	56.2	82.4	31.2	75.7
Tepe, BC	Triple Francis	2.86	12.59	2.72	1.62	52.6	82.4	31	77.9
Tepe, NPV	Triple Francis	4.37	15.85	3.18	1.55	54.4	78.4	31.4	74.2
Tepe, ID	Triple Francis	3.97	14.72	2.91	1.54	49.6	75.2	32.2	71.3
Tepe, ID*	Triple Francis	3.97	14.72	3.19	1.63	55	81.6	28.8	76.4
Karacay, MR	Dual Pelton	2.43	7.59	1.38	1.48	43.4	74.8	27	72
Karacay, BC	Dual Pelton	2.17	7.02	1.28	1.48	42.4	74.8	26.8	72.7
Karacay, NPV	Dual Pelton	3.1	8.8	1.5	1.43	40.8	70.4	26.4	69.1
Karacay, ID	Dual Pelton	2.94	8.39	1.4	1.42	38.8	67.6	24	66.1
Karacay, ID*	Dual Pelton	2.94	8.39	1.52	1.47	42.6	72.4	27.8	71.3
Kaplan, MR	Dual Pelton	3.33	11.58	2.64	1.69	42.2	72	29.6	74.2
Kaplan, BC	Dual Pelton	2.6	10.35	2.43	1.72	39.0	70.4	27.8	73.5
Kaplan, NPV	Dual Pelton	3.62	11.98	2.67	1.66	42	70.8	30.2	74.2
Kaplan, ID	Dual Pelton	3.61	11.78	2.58	1.64	39.8	68.4	29	72.7
Kaplan, ID*	Dual Pelton	3.61	11.78	2.71	1.69	41.8	70.8	30.8	75

the Besik case, namely most robust according to RM_{PB} (MR), maximum NPV, maximum BC, identical turbine with a 10% discount applied to the cost of electro-mechanical equipment (ID*) and without the discount (ID) for each of case-studies listed in Table 3. Buyukdere and Kaplan projects feature a significant head drop and a relatively low flow rate, making the Pelton turbine the only viable option, with a number of turbines (two) suitable for the sites' flow variability (see Figure 1). At the Karacay site, both Pelton and Kaplan turbines are viable options. However, the presence of significant flow variability makes the Pelton turbine a better alternative. For all three sites, the costs of a third Pelton turbine outweigh the added flexibility. Conversely, at the Tepe site, the high CV makes a third turbine valuable, whereas the high flow rate and small gross head makes Francis the sole feasible choice. It is worth noting that for all sites, all the design alternatives recorded in Table 3 have the same turbine number and type. Yet, there is no indication this finding would generalize to other plants.

Besides the robustness metrics themselves, Table 3 also shows robustness for favorable socio-economic futures. For RM_{PB} this corresponds to a cost overrunsscaling factor smaller than 2, whereas forRM_{NPV} these futures feature a cost overrun scaling factor lower than 2 and an interest rate scaling factor lower than 1. The difference between robustness metrics across all futures and in favorable futures only underlines that financial robustness is well below 40% across sites and designs in unfavorable futures. Among the alternatives, BC solutions have smaller design characteristics resulting in lower design cost and an average annual energy output in all cases. Furthermore, BC solutions generally exhibit superior robustness performance than NPV solutions with higher

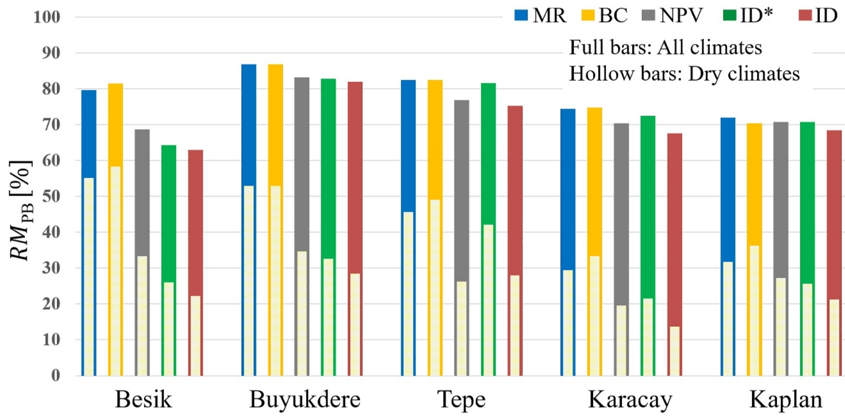

Figure 12. Robustness of the most robust (MR) alternative and the alternative with highest NPV and BC, identical turbine alternative with (ID*) and without discount (ID) of each case study where cost overrun scaling factor <2, with full bars (all climates) and hollow bars (mean flow <75% of historical conditions).

design costs and yearly energy output, even though this advantage tends to disappear under favorable socio-economic futures. Besides, the ID solutions with higher initial cost has the lowest RM_{PB} and RM_{NPV} due to less operational flexibility. This indicates that high sensitivity to the reduction in cash flow caused by drier conditions.

In Figure 12, we further examine favorable socio-economic futures for RM_{PB}. Payback-based robustness is quantified by considering all climates (full bars) and dry climates whose mean discharge values is lower than 75% of the long term mean observed flow (hollow bars). It is evident that if robustness is quantified by only considering dry futures where the additional cost increase is limited the performance of identical turbine configuration decreases drastically in all cases. What is more, the advantages of smaller designs become increasingly apparent across all locations, as BC solutions become more robust than even MR solutions—and recall that MR solutions are the most robust for RM_{PB}. Poor performance of NPV alternative is also observed when compared to the MR and BC solutions. Similarly, in Figure 13, we focus on robustness metric RM_{NPV} and futures with low cost overruns (scaling factor lower than 2). Robustness is quantified by considering all climates (full bars), dry climates whose mean discharge values is lower than 75% of the long term mean observed flow (hollow bars) and risky futures whose interest rate values is bigger than the current rate (black dots). Similar to what happens for RM_{PB}, the BC alternative outperforms other alternatives in dry futures. In fact, it maintains a performance level above 60% across all five sites assuming cost overruns are limited. Yet, when a drier future also features high interest rates (over 9.5% per year), success rates fall across design alternatives and sites. This

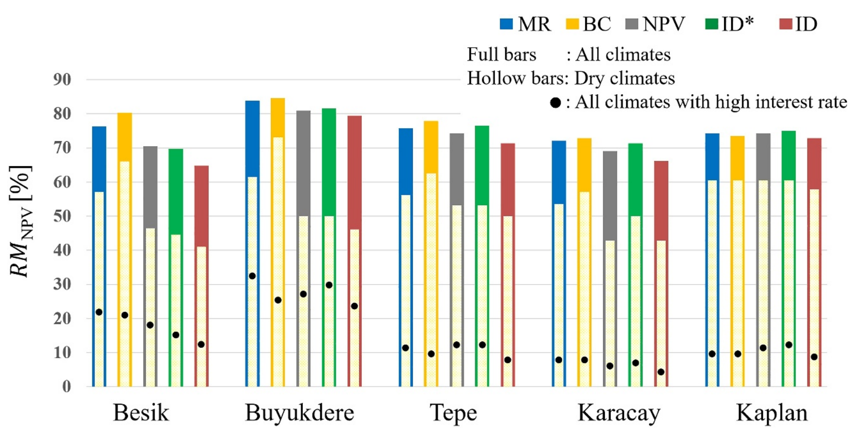

Figure 13. Robustness of the most robust (MR) alternative and the alternative with highest NPV and BC, identical turbine alternative with (ID*) and without discount (ID) of each case study where cost overrun scaling factor <2, with full bars (all climates), hollow bars (mean flow <75% of historical conditions) and black dots (interest rate scaling factor >1).

highlights that dry, economically unstable futures might be a bleak environment for RoR hydropower investments regardless of the other climatic and socio-economic factors.

6. Discussion

This discussion focuses on several important aspects from the preceding section where we demonstrated analysis results of the HYPER-MORDM framework using five different case studies. The findings highlight that RoR based traditional hydropower design which typically rely on optimizing the net present value (NPV) and employing identical turbine configurations exhibit less robustness to both climate change (and associated drying) and to uncertain socio-economic conditions than smaller design alternatives with less installed capacity. This emphasizes the need to update traditional RoR hydropower planning methods to promote the financial robustness of hydropower investments. The rest of this discussion presents several key insights derived from the results, in particular for research and practice of hydropower design.

Before that, a key limitation of our work needs to be discussed. Indeed, even though the HYPER-MORDM framework is of general applicability for RoR hydropower design, the numerical results illustrated in the results section refer to only five cases proposed to be built in the same country. This is sufficient to expose the limitations of traditional design practices, but does not grant general applicability to results. Türkiye boasts abundant topography—making it favorable for hydropower—and varied climates, yet the insights we got from these five cases would need to be applied to other RoR plants to gain generality. Indeed, projects in different regions face not only distinct climate, socio-economic and regulatory environments, but also very different uncertainties—recall that many uncertain factors and their ranges were context specific. An obstacle here is that both optimization and robustness analysis require a considerable amount of computing time and resources, necessitating the use of High performance computing (HPC). This remark is general to exploratory studies of multi-objective trade-offs and robustness studies in water resource systems (e.g., Quinn et al., 2018; Schmitt et al., 2018). In this work, the computational time required to conduct optimization and analyze robustness for the experimental setup discussed in the previous section (optimization: 1,000 years of synthetic daily discharge data using 100,000 function evaluations, robustness across $S = 500$ SOWs) for a single case is around 120 hr. Note this is just the final version of our study, it follows several runs featuring a similar computational effort for each site. Extension to hundreds of potential RoR sites thus necessitates large amounts of computational resources. Though often key to unlocking new insights in complex water resource systems, this use of computational power contributes to the continuous growth of data center demand, which currently account for 0.3% of global carbon emissions (Cao et al., 2022; Jones, 2018). This proportion is expected to rise in the future (Katal et al., 2022), posing an additional, significant challenge to global climate change mitigation efforts. Workarounds to drastically reduce the computational costs for both optimization and robustness analysis of these plants would facilitate the application of the approach to a greater number of plants and lead to more general conclusions, while limiting the need for high-performance computing.

Small sample size aside, our analysis suggest that turbine configurations significantly impact the overall robustness of a project (see in particular Table 3). This is because larger installed capacities aimed at making the most of above-average flow conditions are more expensive while lacking the flexibility to capture low flows—at demonstrated in Figure 8. There is a need for understanding how these lessons derived for RoR plants could apply to reservoir-based (RB) plants. In RB plants, operators can control the flow but head variations are widely expected to intensify in a drought-prone world. These head variations impact the efficiency of turbines designed for a nominal head typically corresponding to a full reservoir—as mentioned for the Colorado River reservoirs in the introduction. This means there could be opportunities for designing turbines for different head conditions. Yet, the majority of the RB hydropower literature ignores turbine system efficiency during the design of the dam and hydropower plant system. Typically, the selection of the turbine configuration typically takes place after determining the installed capacity (DSI, 2012) due to the added complexity of the turbine system design process. This lack of integration of turbine efficiency into design extends to recent research (e.g., Bertoni et al., 2019, 2021; Ray et al., 2018), and this can lead to a mismatch between projected and actual energy production, even when operations are explicitly simulated. Adapting the HYPER-MORDM framework would facilitate the identification of robust alternatives capable of addressing the dynamic nature of these factors and effectively overcoming these challenges.

What is more, the aging hydropower infrastructure presents a significant challenge, with approximately one-fifth of installed hydropower turbines, accounting for around 154 GW, will be more than 55 years old by 2030 globally

(IEA, 2021). Many of these turbines will need to be replaced to maintain high plant performance, and this will lead to opportunities to retrofit hydropower plants to improve their flexibility and meet changing and variable hydrological conditions. The need for a well-defined methodology to effectively evaluate and select the most appropriate turbine replacement or upgrade options is evident across both RoR and RB plants. To meet these needs, the approach proposed here should be expanded not only for RoR retrofit, but also to turbine system optimization for design and retrofit of RB hydropower plants. These extensions of our approach would also need to account for hydropower plant maintenance. The multipurpose nature of many reservoirs and the fact that hydrological variability and drought impact RoR and RB hydropower differently are significant challenges that this latter extension of the HYPER-MORDEM approach will need to tackle.

RoR installations, even though their environmental footprint is minimal when compared with that of reservoirs (Fearnside, 2014; Kishore et al., 2021; Kosnik, 2010; Yildiz et al., 2021), are not impact-free. In particular, cascade RoR plants on the same river have a significant compounding effect on river ecosystems, even though their storage capacity is negligible (Finer & Jenkins, 2012; Jaccard et al., 2011; Kelly-Richards et al., 2017). Environmental downsides mean that this kind of project should be approached with extreme caution if their financial robustness is not guaranteed. This uncertain financial robustness was apparent across all five of our case-studies, and could plausibly be present in other regions where the best sites for hydropower have already been developed. In particular, our findings suggest that the financial robustness of proposed hydropower projects often hinges on favorable socio-economic conditions. If the outlook for interest rates is uncertain, or if investors are not sure of how the factors that lead to high cost overruns are managed, considering not developing the site might be a wise option given potential environmental impacts. Cost overruns are determined by underlying geology and a mix of environmental, social and management factors leading to design revisions (e.g., Ansar et al., 2014; Ray et al., 2018; Sovacool et al., 2014)—considering not developing the site might be a wise option given potential environmental impacts. In fact, environmental issues, along with site geology, have been identified as the foremost risks to hydropower projects (Kucukali, 2011). A possible extension of our framework for real-world application should integrate the environmental risk assessment into the analysis.

7. Conclusions

This paper introduces the HYPER-MORDM approach, which combines global optimization with multiobjective evolutionary algorithms (MOEAs) and many objective robust decision making (MORDM). This is to tackle the challenges associated with run-of-river (RoR) hydropower plant design under deep uncertainty, in order to (a) provide insights into potential trade-offs between design objectives and (b) to explore the financial robustness of alternatives. This research advances conventional RoR hydropower plant design, which typically relies on cost-benefit analysis, by incorporating recent advancements in decision-making under deep uncertainty. It is also the first study to explicitly incorporate variable turbine efficiency into the robust design of hydropower plants, including reservoir-based hydropower plants.

Applying HYPER-MORDM to five planned RoR hydropower plants planned in a range of hydro-climatic regions of Türkiye led to several insights on robust RoR plant designs. Results confirm earlier findings that installation of more than one turbine in a hydropower plant enhances power production significantly by providing operational flexibility in the face of variable streamflows. This finding aligns with current industry practices, where the consideration of multiple turbines is common due to the simplicity of installation, maintenance benefits, and ensuring a minimum level of operation if economically feasible. When contrasting robustness of a design with its NPV, designs with the highest NPVs tend to focus on harnessing above-average flows, but this comes at the expense of financial robustness in the face of both climate change (and associated drying) and to evolving financial conditions. In contrast, maximizing the benefit cost ratio (BC) yields more financially robust solutions than maximizing NPV, as it leads to less costly designs that generate slightly less revenue on average, but with increased flexibility to better exploit low flows. Traditional design approaches using identical turbine configuration and NPV maximization have been shown to be significantly more vulnerable to climate change, and identical turbines can lead to inferior designs even under historical conditions. This is due in a large part to a less flexible configuration. These results hold even when applying a significant 10% discount on the cost of electro-mechanic equipment. Another consequential finding is the importance of non-climatic factors, which can be more crucial than climatic ones in determining a design's financial robustness. High cost overruns have been found to often make a project non-viable and are often overlooked in the hydropower design literature. High cost overruns often reflect poor project management, including overlooking social and environmental constraints, and errors in screening a site's geology before the start of construction.

Last but not last, this study adds to a growing body of literature stressing the importance of considering multiple uncertainties in combination, and it demonstrates it for the financial robustness of RoR plant design. Taken together, these results suggest that applying HYPER-MORDM approach in the design of run-of-river hydropower plants provides water resource planners and decision makers a comprehensive framework to make informed decisions regarding the implementation of these projects and determining the most robust design alternative under deep future uncertainties. This work also stresses the need for considering turbine efficiency in hydropower plant design, including when they are part of a reservoir system. This is currently not the case, even in the middle of a global hydropower boom, and as many existing plants, large and small, will need to upgrade their turbine systems in the coming years.

Data Availability Statement

All the data related to the five case studies, including the input parameters, the MATLAB scripts for multi-objective optimization, and robustness analysis, are openly accessible from the Zenodo open-access repository (Yildiz, Brown, & Rougé, 2024) at https://doi.org/10.5281/zenodo.10627287. Additionally, presented robustness analysis data for each case study are provided in the University of Sheffield's data repository due to their large size (Yildiz, Rougé, & Brown, 2024) at https://doi.org/10.15131/shef.data.23703864.v2. The repository includes the pre-calculated robustness results, allowing researchers to review and analyze the robustness without the need to re-run the analysis.

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