

1. Abstract

We investigate the design of small hydropower plants under multiple sources of uncertainty and contrast it with the conventional deterministic practice that leads to a unique solution. In particular, we emphasize three sources of uncertainty, referring to: (a) the rainfall process, (b) the rainfall-runoff transformation, and (c) the flow-energy conversion. The first is due to the natural (i.e., hydroclimatic) variability, and is represented through stochastic approaches. The rainfall-runoff uncertainty arises from inherent structural shortcomings and poor parameter identifiability across the calibration procedure. In fact, hydrological model parameterizations using only historical data are often insufficient for accurately predicting catchment behavior over the long term, as they may not capture the full range of hydroclimatic conditions that the catchment may be subjected to. To address this issue, we use synthetic time series as drivers to parameterize the model and validate it against observed data. This approach preserves the observed data's probabilistic properties and dependence structure while also providing a much wider range of hydroclimatic conditions for model training. In addition, it allows for assessing and quantifying the total model uncertainty. The final source of uncertainty is depicted by means of probabilistic efficiency curves. This Monte Carlo simulation-optimization framework is formalized as a modular procedure, the different sources of uncertainty and the full context are tested through the design of a small hydropower plant in Epirus, Western Greece.

2. Problem statement

The conventional design of SHPPs follows a fully deterministic procedure, thus all derived techno-economic quantities and associated decisions are subject to all kinds of data and model limitations. The ignorance of uncertainty introduces significant risk, both from the engineering and the investor's perspective.

In order to tackle this issue, we establish a modular scheme to represent the following major sources of uncertainty:



3. The spark for delving into the uncertainty...

As part of our undergraduate ninth-semester course "Integrated Project in Hydraulic Engineering", we implemented the conventional design of a run-off-river hydropower plant in Arachthos river basin, Epirus, NW Greece, comprising the following steps:

- Search for alternative siting locations and preliminary evaluations across the watershed, based on macroscopic data (catchment area, head, diversion length) and legal constraints, and establishment of four potential layouts.
- II. Hydrological analysis of upstream catchments (collection of point rainfall and temperature data, areal integration of rainfall through the Thiessen polygon method, estimation of potential evapotranspiration).
- III. Development of a lumped conceptual rainfall-runoff model and estimation of its parameters through calibration against observed runoff data, obtained by neighboring hydrometric stations.
- IV. Application of optimized parameters for the generation of historical daily inflow series at the proposed sites, for a 20-year period.
- V. Optimization of turbine mixing for each proposed layout, following the rationale by Sakki et al. (2022b), to assess key technical and economic quantities (mean energy production, capacity factor, cost of turbines, anticipated profits).
- VI. Selection of the most advantageous layout, detailed design and economic assessment.

Although we found the overall design procedure quite rigorous, we noticed that it lacked the consideration of uncertainty, which is omnipresent in multiple forms in nature (especially in hydrology) and across all aspects of sociotechnical systems.



Design of small hydropower plants under uncertainty: from the hydrological cycle to energy conversion EGU General Assembly 2023, Vienna, Austria, 23-28 April 2023; Session HS5.6: Innovation in Hydropower Operations and Planning to Integrate Renewable Energy Sources and Optimize the Water-Energy Nexus P. Pagotelis*, K. Tsilipiras*, A. Lyras*, A. Koutsovitis*, G.-K. Sakki and A. Efstratiadis *Contributed Equally

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- The design procedure of the hydropower system is driven by daily streamflow time series, which are which is in turn driven by precipitation and potential evapotranspiration data.
- In the absence of hydrometric information at the site of interest (intake), the inflows are extracted through a conceptual rainfall-runoff model that employs a typical bucket-type scheme, comprising three interconnected tanks, as well as a linear reservoir that employs the propagation of the surface runoff (estimated by the NRCS-CN method) to the catchment's outlet.
- The model contains four parameters that are inferred via a conventional calibration approach, based on observed data quite downstream of the site of interest (Pournari dam).
- The calibration ensures good model performance (NSE = 80%).
- The overall watershed is homogenous with respect to its physiographic characteristics, thus the optimized model parameters can be considered representative across the entire area.



5. Setup of rainfall-runoff model calibration under uncertainty

- The model parameters are inherently uncertain, since they are inferred through calibration. • We investigate two key sources of uncertainty within the calibration procedure, arising from the input data and the formulation of the objective function.
- In this vein, we employ 1000 independent calibration runs in a Monte Carlo context:
 - we randomly select half of the observed streamflow data to feed the calibration, through a randomly moving window of 10-years length;
- we formalize a multi-objective function comprising three metrics (Persistence Index, High Flow Index, Nash-Sutcliffe Efficiency; Fereira et al., 2020) and assign random weights to them.
- Outcome of this exercise are 4000 optimized parameter sets that are by definition equifinal.
- The parameter uncertainty is easily visualized by means of empirical histograms.



The parameters are also significantly correlated. This fact, which is usually ignored in hydrological model uncertainty analyses, introduces further complexity, and it becomes crucial to adopt stochastic instead of simpler probabilistic approaches, in order to account for cross-dependencies.

6. Optimizing the turbine mix under uncertainty

- For a given layout of the hydropower system (i.e., siting of intake and power station, delineation of conveyance system, and selection of penstock diameter), the most important design decision involves the selection of turbine capacity. Usually, two turbines of different power capacity are applied, each one operating within a specific flow range, in order to ensure the maximum possible exploitation of the available hydropower potential (Sarantopoulou et al., 2022).
- stochastic behavior of the observed data, as well as the Hurst-Kolmogorov dynamics, which is the footprint of the perpetually changing, and thus uncertain, climate.
- The mixing of turbines is a challenging design task, which can be formalized as an optimization problem, while here this is configured in an uncertainty-aware context. • Initially, we generate a synthetic rainfall time series of 2000 years length through the anySim package (Tsoukalas et al., 2020), thus reproducing the probabilistic and • We run the design optimization problem multiple times, by configuring equally-probable scenarios, as follows:
- We apply a randomly-moving window of 20-years length to select a subset of the synthetic rainfall record.
- We use this subset as input to the rainfall-runoff model, next running with randomly-selected parameters, to provide stochastic streamflow data at the intake. • Within the simulation of the SHPP operation, we apply the turbine efficiency formula, introduced by Sakki et al. (2022a):

$$n_T = n_{min} + \left(1 - \left(1 - \left(\frac{q/q_{max} - \theta}{1 - \theta}\right)^a\right)^b\right) (n_{max} - n_{min})$$

where n_{max} , n_{min} are the upper and lower efficiency values, $\theta = q_{min}/q_{max}$, and a, b are shape parameters that change according to the turbine type. These are considered as random variables, which are picked from a Gaussian distribution with mean values of a = 0.78 and b = 3.11 (typical values for Francis-type turbines), and a coefficient of variation of 0.10. • The objective function accounts for turbine costs and benefits from hydropower production, both

expressed on annual basis. The depreciation costs are estimated by:

$$D = C \frac{i(1+i)^n}{(1+i)^n - 1}$$

where i is the rate of interest, C is the cost of turbines (function of power capacity and head; cf. Aggidis et al., 2010), and n is the expected recuperation period of the electromechanical equipment (five years). The uncertainty within cost calculations is expressed by means of a randomly varying interest rate, which is sampled from a uniform distribution, within the range 3-6%.



In order to run the model under parameter uncertainty, we fit suitable marginal distributions to each parameter and establish a copula-based scheme to generate correlated pairs of parameters.

Outcomes of conventional design

- Turbine type: Francis
- Turbine mix: 2075 + 690 kW
- Total capacity: 2765 kW
- Mean annual energy: 5.11 GWh
- Capacity factor: 21.1% Mean annual revenue from power
- production: 460,026 € Cost of E/M equipment (CAPEX): 1,403,234 €
- Interest rate for depreciation of CAPEX after n = 5 years: 5%
- Net profit (optimized): 135,915 €



8. Discussion & future research

References



between the total capacity and the net annual profit. This graph is significantly useful from the investor's perspective. For a given design, one can quantify the risk of the investment, in terms of uncertainty bounds.



The distribution of the total installed capacity has a slightly skewed scheme. The conventional design results in a little smaller total capacity than the Monte-Carlo mean, and also yields a slightly larger annual profit than the average solution.

• This research was focused on a specific SHPP design project, affected by its unique local hydrological conditions. We examined four distinct causes of uncertainty, while in reality there are several others to be embedded in the stochastic design procedure. • The outcomes of our SHPP study under the guise of uncertainty indicates that whilst the conventional design can still yield a viable result that falls within a logical range, uncertainty should always be taken into account in order to provide well-established quantifications of the associated risks.

• Future research may also address the uncertainty of all other economic aspects of the design procedure, of the investment risk of a SHPP, and the drop of the turbine efficiency due to ageing effects.

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