European Geosciences Union General Assembly 2021, online, 19-30 April 2021

HS5.3.3: Innovation in hydropower operations and planning to integrate renewable energy sources and optimize the Water-Energy Nexus

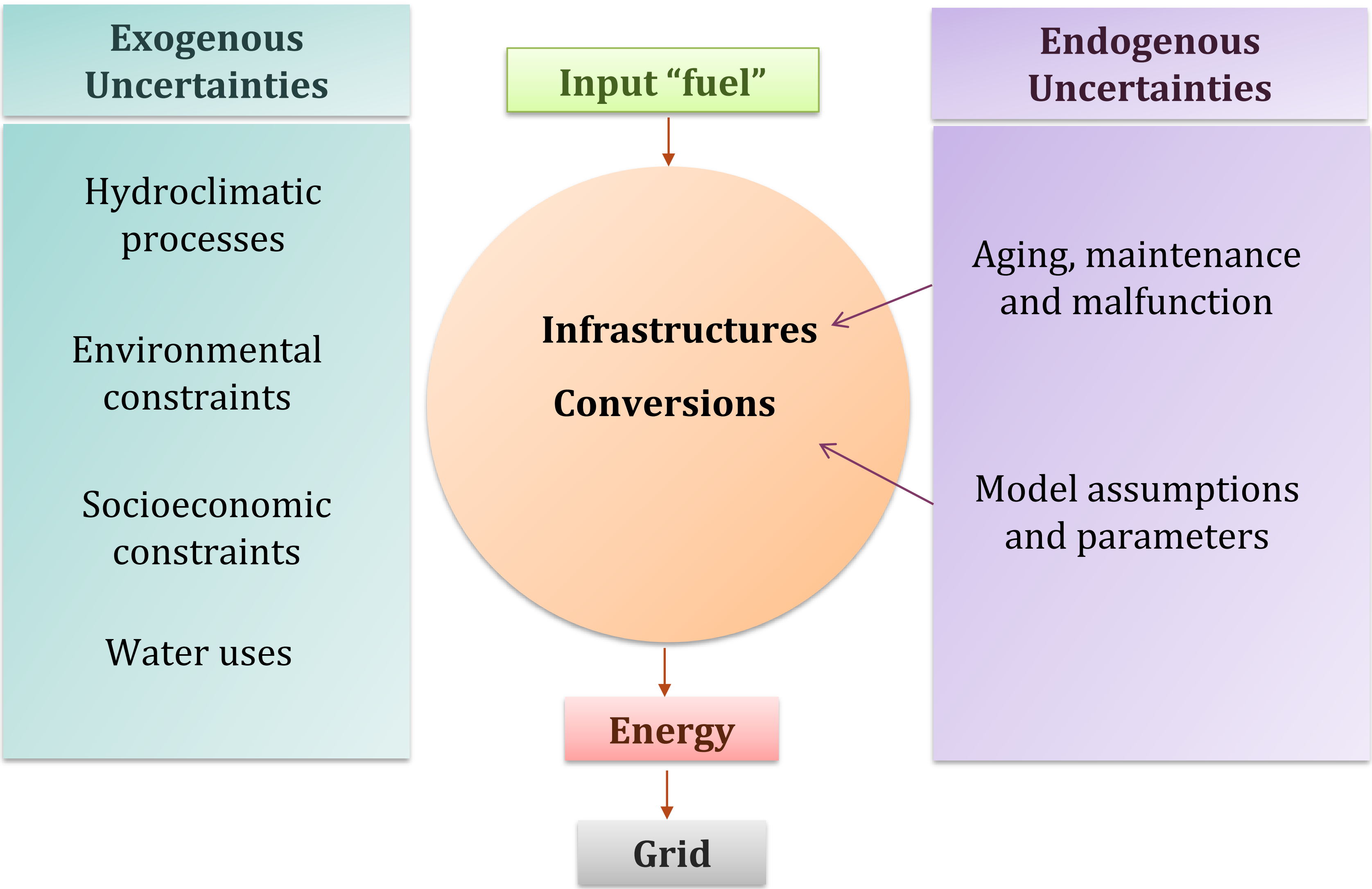
A dilemma of small hydropower plants: Design with uncertainty or uncertainty within design?

Georgia-Konstantina Sakki, Ioannis Tsoukalas, Panagiotis Kossieris, and Andreas Efstratiadis

Department of Water Resources & Environmental Engineering, National Technical University of Athens, Greece

Presentation available online: https://www.itia.ntua.gr/2101/

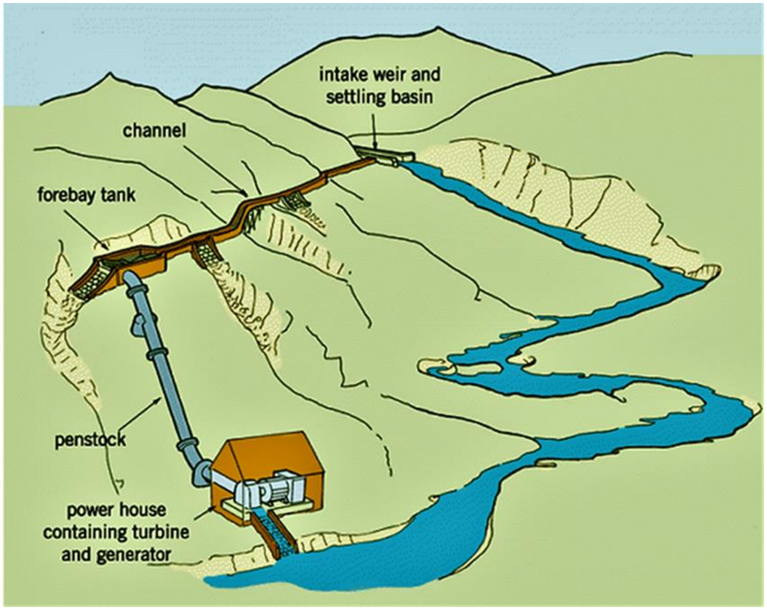
Overall motivation: recognizing uncertainties in the project life of renewable energy systems



Specific target: embedding uncertainties in the design of small hydropower plants

Setting the design of small hydropower plants

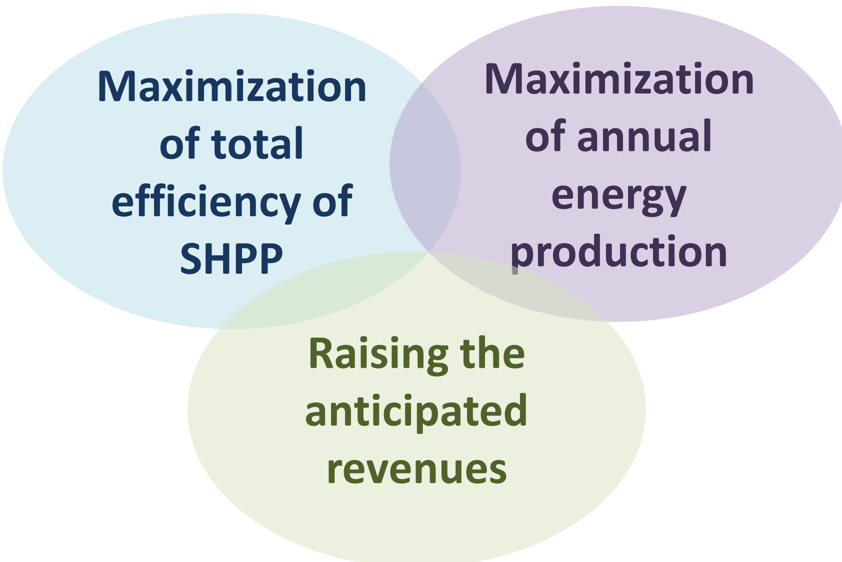
- To define a hydroelectric plant as small, the installed power capacity of the turbines must be under a certain limit, determined by the national legislation (15 MW in Greece).
- The common type of small hydropower plants are the so-called **run-of-river** (RoR) that take advantage of the elevation difference between the intake and the outflow site.
- Due to their negligible storage capacity, RoRs do not employ regulation; in particular, the arriving flow is diverted and delivered under pressure to a downstream power station.
- In the context of **siting and layout** of RoRs, key design objectives are:
  - maximization of discharge;
  - maximization of head (elevation difference between the intake and the outflow site);
  - minimization of diversion length.
- RoRs are subject to two major issues, associated with the **turbine type** and the **power capacity**:
  - they only exploit part of inflow between a minimum and a maximum value;
  - in this feasible range, the turbine efficiency is highly varying, according to a rated flow.



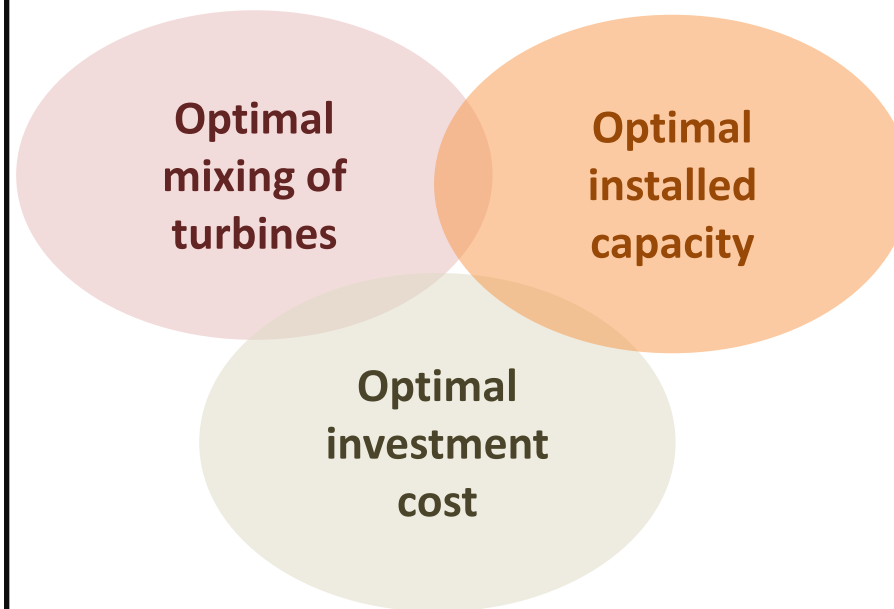
- As result of the above peculiarities, the typical design practice in turbine selection is the **mixing of two turbines**, preferably of different capacity.

The design challenge in a nutshell

Objectives



Result



Research questions within turbine mixing optimization:

- Definition of performance metric, ensuring a sustainable compromise between the investment costs and the expected revenues;
- Effective and efficient incorporation of uncertainty within optimization;
- Assessment of impacts of uncertainty within design;
- Interpretation of uncertainty in practice.

RoRs in a simulation context: overview

- Input data:
  - Streamflow time series at the intake, q, after subtracting environmental flows;
  - Gross head, h (practically constant);
  - Power plant efficiency, $\eta(q)$, expressed as function of discharge;
  - Maximum discharge that can pass from the turbines (nominal flow), $q_{i,max}$
  - Minimum discharge for energy production, $q_{i,min}$ (typically, 10-30% of $q_{i,max}$)
- In the generic case we consider two turbines of power capacity, P_1 and P_2, operating within flow ranges $(q_{1,min}, q_{1,max})$ and $(q_{2,min}, q_{2,max})$, respectively.
- The maximum (nominal) discharge of each turbine is given by:

$$q_{i,max} = \frac{P_i}{\gamma\, \eta_{i,max}\, h_n}$$

  where $\eta_{i,max}$ is the total efficiency at the maximum discharge, which depends on the turbine type, γ is the specific weight of water (9.81 KN/m^3) and h_n is the net head, i.e. the gross head, h, after subtracting hydraulic losses, h_L.
- Hydraulic losses include friction and local ones, which are function of discharge and the penstock properties (roughness, length, diameter, geometrical transitions).
- The minimum discharge of each turbine is expressed as ratio of the maximum one, i.e.:

$$q_{i,min} = \theta_i\, q_{i,max}$$

RoRs in a simulation context: computations

- We consider a **hierarchical operation** of the two turbines, where the flow passing from the first one is given by:

$$q_{T1} = \min(q,\ q_{1,max})$$

- If $q > q_{1,max}$ then the surplus flow passing from the second turbine is:

$$q_{T2} = \min(q - q_{T1},\ q_{2,max})$$

- The hydraulic losses and thus the net head, h_n, are estimated as function of the total discharge, $q_{T1} + q_{T2}$, which is diverted to the turbines.

- For $q_{Ti} < q_{i,min}$ the turbine is set out of operation, while for $q_{Ti} > q_{i,min}$ the energy produced by each turbine is:

$$E_i = \eta(q_{Ti})\,\gamma\, q_{Ti}\, h_n\, \Delta t$$

where Δt is the time interval of calculations and $\eta(q_{Ti})$ the flow-dependent total efficiency of each turbine, which is either expressed analytically (Sakki *et al.*, 2020):

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

where a and b are shape parameters that change according to the turbine type.

Depreciation of turbines as performance metric

- For a given configuration of major system components (intake and power station sites, layout of diversion), the investment costs are directly associated with the turbine capacity, also affecting the maximum discharge and thus the sizing of the water transfer system.
- On the other hand, the mean annual energy is associated with the anticipated revenues from the operation of the power system.
- In this context, we propose an optimization function, aiming at the **maximization of the net annual profit**, estimated as the difference:

$$F = u\,E - D$$

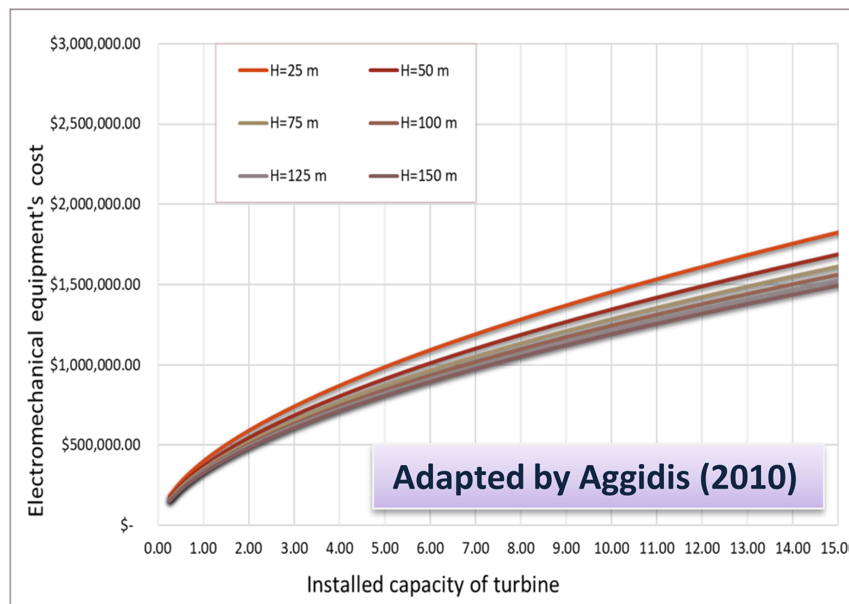
where E denotes the mean annual revenues from energy production, is u the unit price of energy, and D is the depreciation of electromechanical equipment (E/M).

- Considering a period of n years with a specific interest rate i, the equal annual instalments for the E/M equipment are estimated by:

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

- The cost of the E/M equipment is linked with the power capacity, P, and the head, h, through the empirical functions of the form:

$$C = a\,P^b\,h^c$$



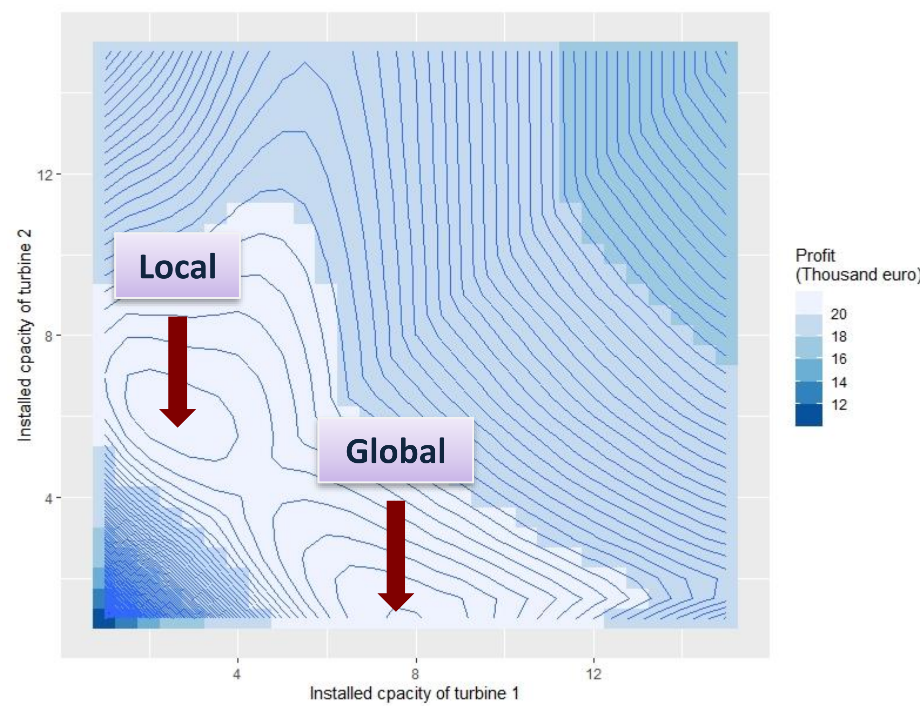
Insights into the design optimization problem

- The design optimization problem aims at specifying the power capacity values of the two turbines that maximize the net annual profit of the system, under the legislative constraint of total allowable capacity for small hydropower plants, P_{max}, i.e.:

$$\text{maximize } F(P_1, P_2)$$

$$\text{s.t. } P_1 + P_2 \leq P_{max}$$

- The response surface of the objective function, F, is strongly nonlinear, resulting into two optimal mixings, (P_1^*, P_2^*), with quite close performance.
- The two optima reveal **two alterative operations** of the hydropower system, one by setting in high priority the large turbine (Global) and the other the small one (Local).
- A **conventional deterministic design concludes to a unique solution**, i.e. the global optimum of the profit function.

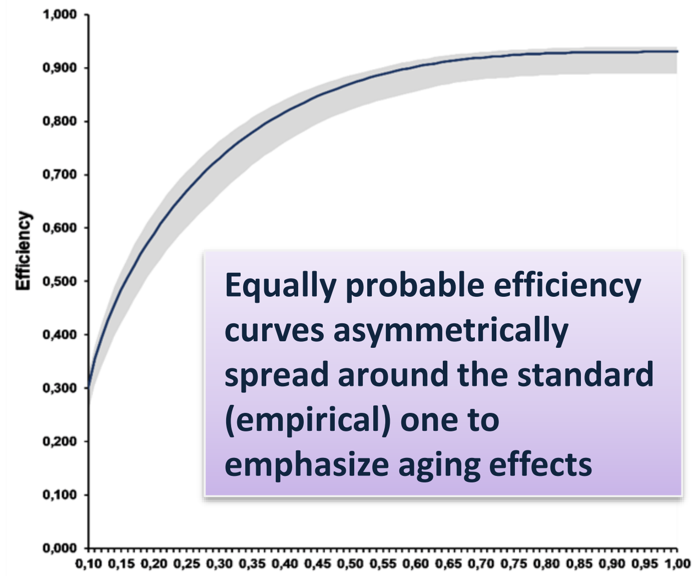


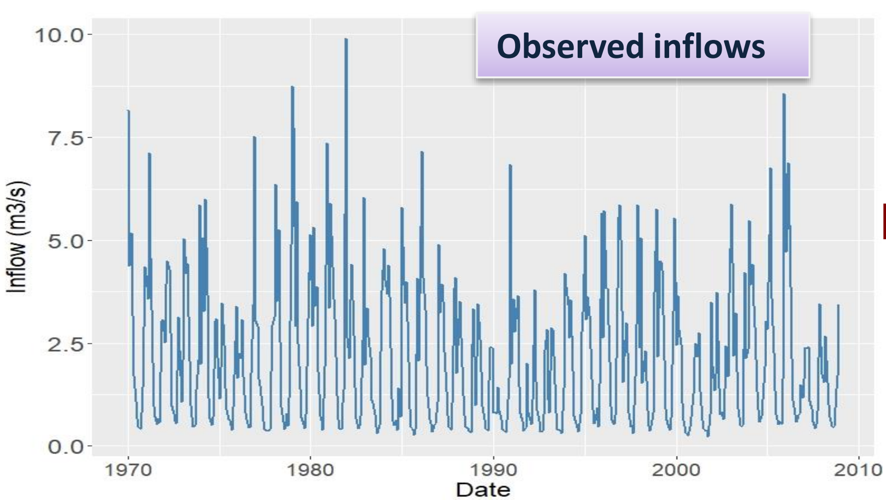
One-million-euro question:

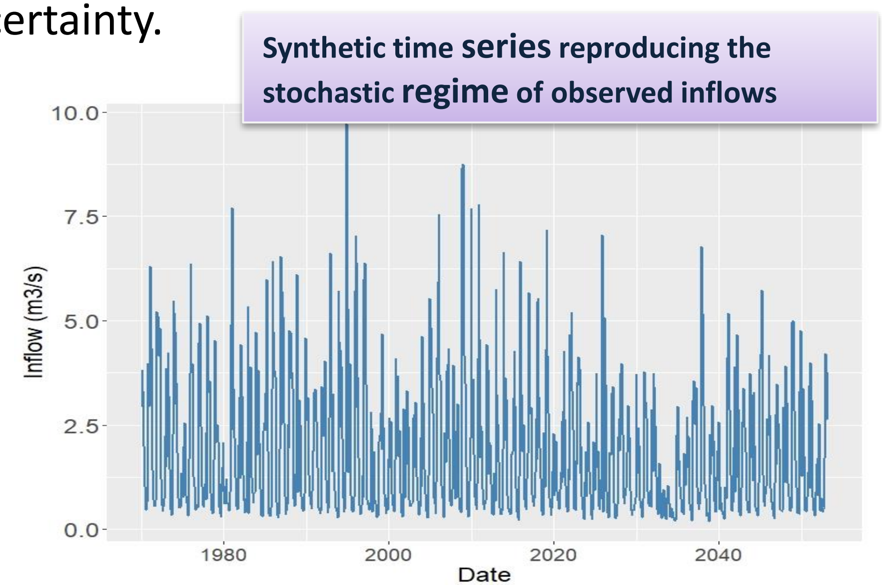
Will the optimal mixing of turbines change if uncertainty is accounted for?

Let’s talk about uncertainty in the design of RoRs

- External uncertainty: **inflows**
  - Process uncertainty;
  - Data uncertainty (sample size and scale).
- Internal uncertainty: **flow-energy conversion**
  - Actual efficiency vs. empirical nomographs;
  - Effects of equipment aging.
- Generic tools to represent uncertainties:
  - **Statistics**, accounting for marginal properties;
  - **Stochastics**, also accounting for dependencies.
  - **Copulas**, for quantifying predictive uncertainty.

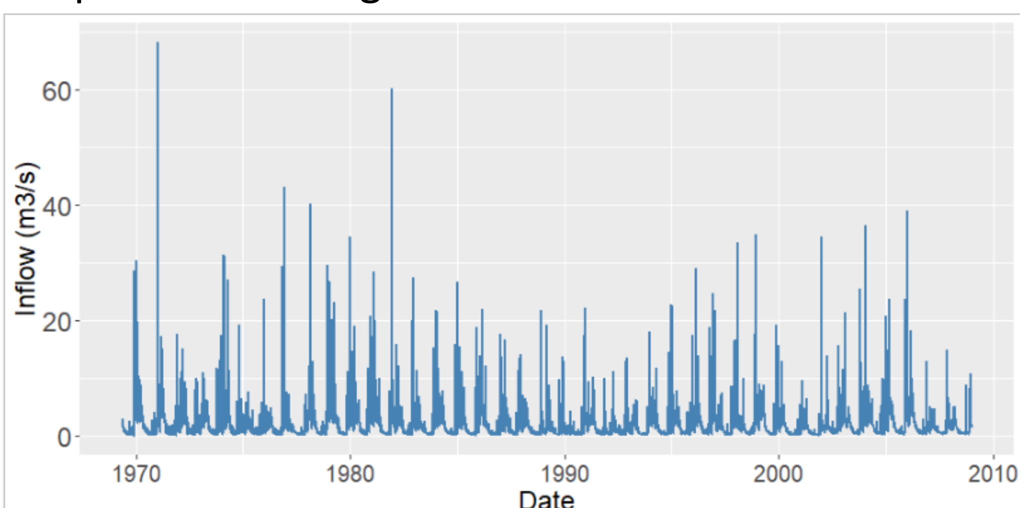


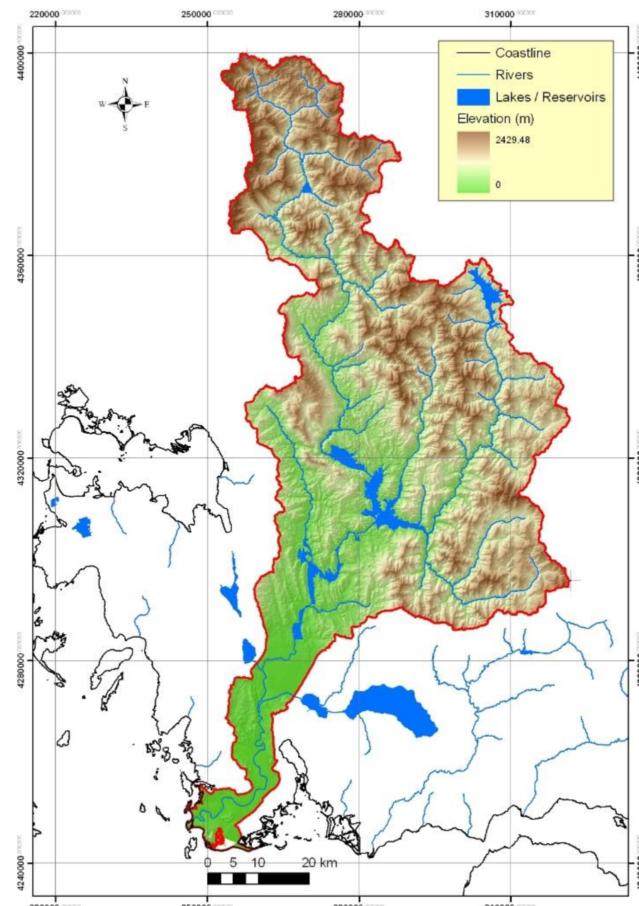




Proof of concept: Design of RoR plant at Achelous

- Run-of-river hydropower plant, in a sub-catchment of Achelous river, Western Greece;
- Sizing of two Francis-type turbines, taking advantage of a gross head of 150 m;
- Daily inflow data for years 1969-2008 (mean annual inflow 2.15 m^3/s);
- Environmental flow 0.25 m^3/s, released downstream of the intake, through the fish passage (30% of mean discharge of September, according to the Greek legislation);
- Inputs of efficiency formula: $\theta = 0.15$, $n_{min} = 0.33$, $n_{max} = 0.93$, $a = 0.78$, $b = 3.11$ (parameters fitted to an empirical nomograph for Francis with $n_s = 100$);
- Cost inputs: $A = 14400$ €, $b = 0.56$, $c = -0.112$;
- Inputs of depreciation formula: n = 10 years, i = 4%.
- Optimized mixing: **11.7 and 2.4 MW**.





Generic scheme for embedding uncertainty within design

- Uncertainty refers either to the inflow (**process uncertainty**) or to the flow-energy conversion formula (**parameter uncertainty**).
- For the representation of the inflow processes uncertainty, which is due to hydroclimatic variability, we employ two alternative approaches for generating 100 inflow ensembles of 20 years (i.e., the economic life of such projects, according to the Greek legislation):
  - **Statistical approach**, by fitting a suitable distribution model to the historical time series (in particular, the Generalized Gamma), next used as data generator;
  - **Stochastic approach**, where we employ the generation scheme implemented within the anySim package (Tsoukalas *et al.*, 2020) that reproduces the probabilistic properties and the auto-dependence structures of the observed data across seasons and across three scales of interest (daily, monthly, annual).
- For the representation of the uncertainty of the standard efficiency formula:
  - We consider its **parameters as random variables**, by assuming that the efficiency bounds $\eta_{\min}$ and η_{max} follow a beta distribution, while the two shape parameters a and b are normally-distributed.
  - We repeat the design procedure by **running each out of 100 inflow scenarios with different efficiency curve**, provided via random sampling of its parameters.
  - The selection of aforementioned distributions ensures that the rated flow - efficiency ensembles are **asymmetrically distributed around the standard curve**, to account for the effects of systematic drop of efficiency due to aging.

Architecture of design optimization under uncertainty

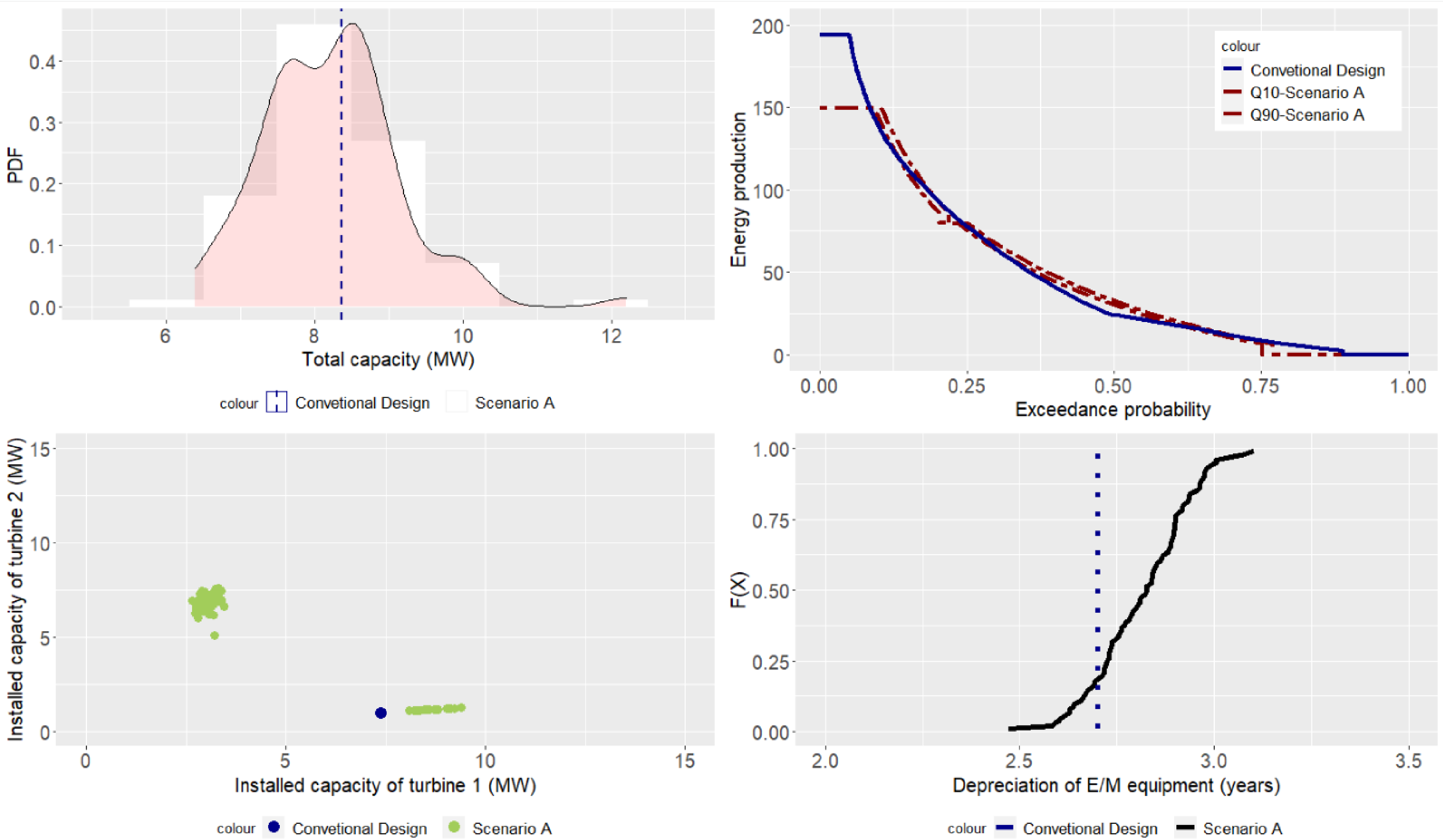
- The design under uncertainty is formalized by means of a **modular scenario-based scheme**, each one resulting to **100 optimized mixings of power capacity values**:

  Scenario A: 100 inflow realizations, provided through random sampling from the Generalized Gamma distribution model;

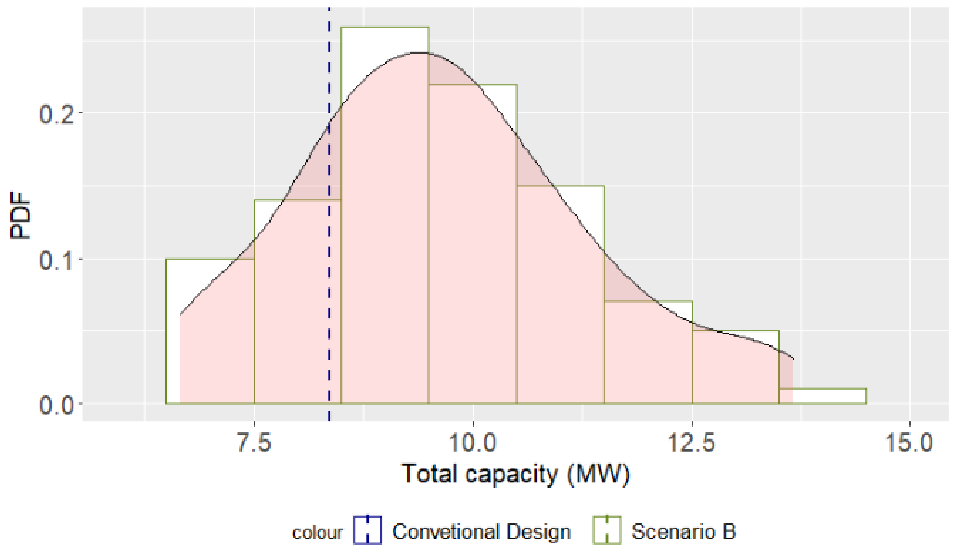
  Scenario B: 100 inflow realizations, generated through the stochastic model;

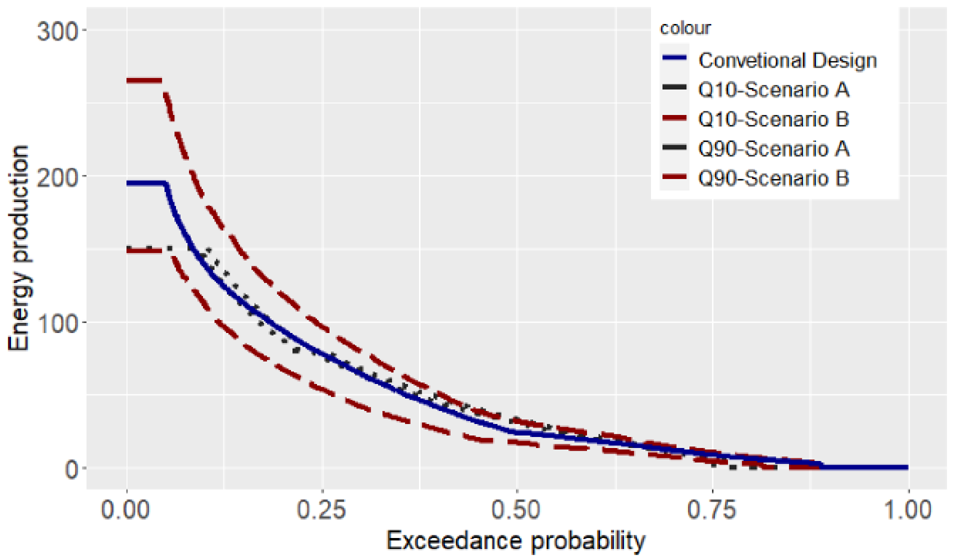
  Scenario C: Combinations of 100 synthetically-generated inflow realizations with 100 randomly-generated efficiency curves around the standard one.
- The above scheme is tested not only with the original daily inflows *per se*, but also by aggregating the data at the monthly time scale, in order to assess the **uncertainty induced by the temporal resolution of the historical time series**.
- For each run of the design optimization procedure, we extract:
  - optimized mixing (design variables) and depreciation (objective function);
  - energy-probability curves;
- For each scenario, we quantify the uncertainty of its optimized outputs, in terms of:
  - **empirical probability distribution** of total capacity and depreciation;
  - **scatter plots** of power capacity values, P_1^* and P_2^*;
  - **empirical quantiles** of energy-probability curves, for 90% confidence intervals.

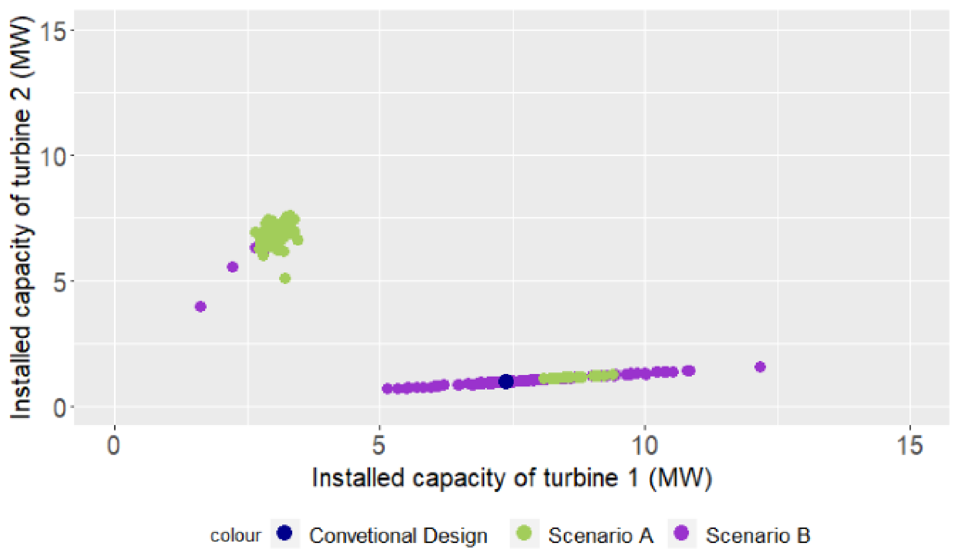
Scenario A: Statistical approach for inflow uncertainty

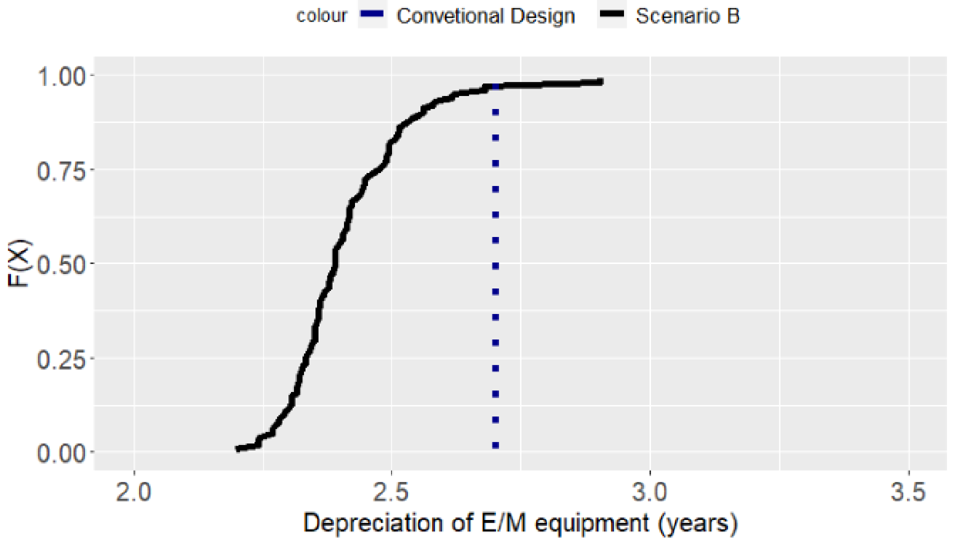


Scenario B: Stochastic approach for inflow uncertainty

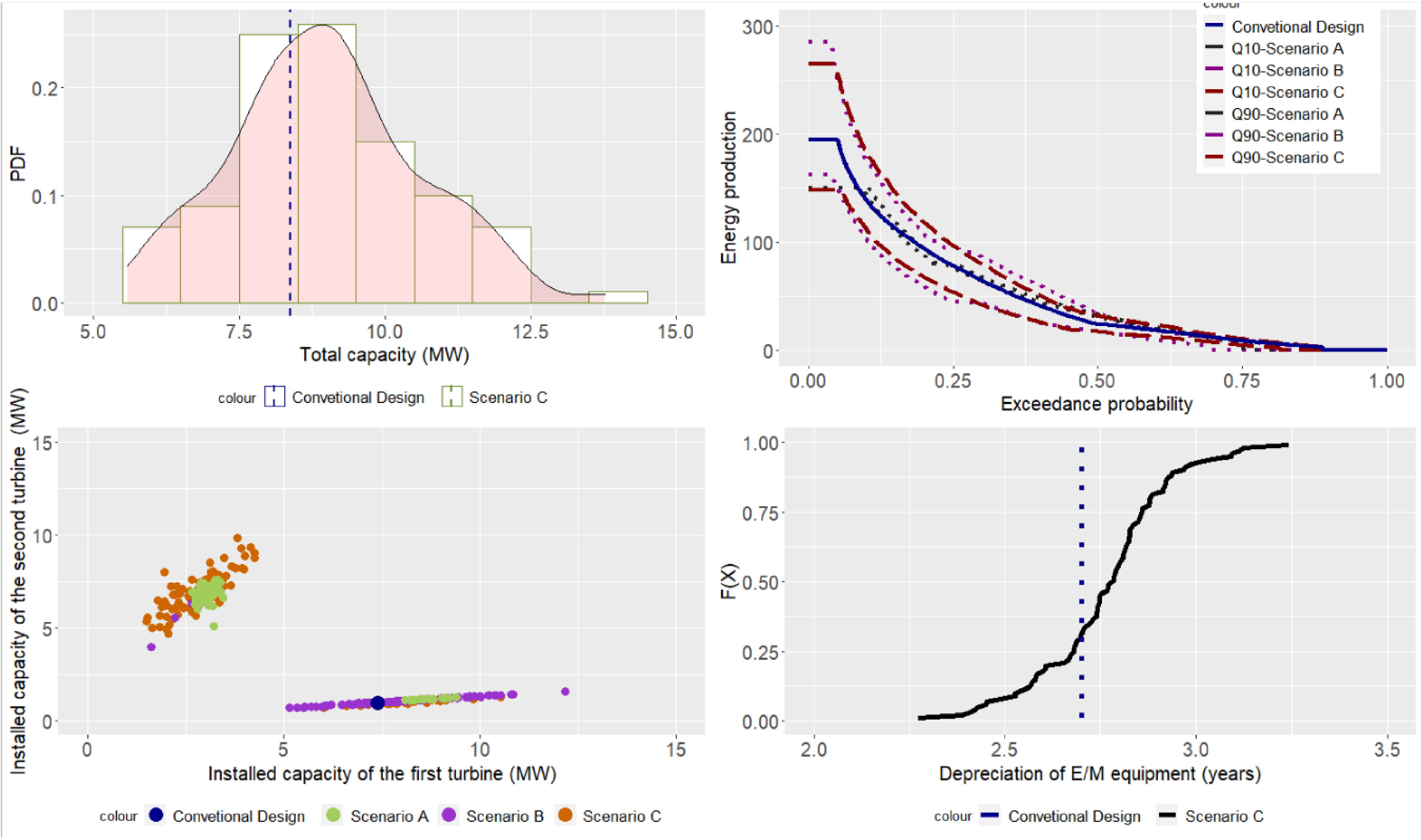








Scenario C: Joint uncertainty of inflow and efficiency



Copula-based modelling of predictive uncertainty [1]

Copulas (Sklar, 1959; 1973) can be particularly useful tools for the quantification of the model's $(\mathcal{M})$ predictive uncertainty, since the allow the derivation of conditional distributions (see, Tsoukalas (2018)). In particular, let Y_O and Y_M denote random variables (RVs) corresponding to the observed and modelled data respectively. Their marginal distributions (CDFs) are denoted by $F_{Y_O}(y_O)$ and $F_{Y_M}(y_M)$. Note that Y^M is a function of our predictive model $\mathcal{M}(\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ denotes its parameters. Further to these, the joint CDF among Y^O and Y^M, can be expressed by,

$$F(Y_O, Y_M) \coloneqq P(Y_O \leq y_O, Y_M \leq y_M) = C\left(F_{Y_O}(y_O), F_{Y_M}(y_M)\right) = C(u_O, u_M)$$

where $C(x, y)$ denotes the copula CDF, as well as $u_O = F_{Y_O}(y_O)$ and $u_M = F_{Y_M}(y_M)$ are uniformly distributed RVs in [0, 1].

In order to quantify the model's $(\mathcal{M})$ predictive uncertainty, the idea is to establish the conditional CDF, $F(Y_O | Y_M = \mathrm{y_M}) \coloneqq P(Y_O \leq y_O | Y_M = \mathrm{y_M})$, that is,

$$F(Y_O | Y_M = \mathrm{y_M}) = \frac{\partial C(u_O, u_M)}{\partial u_M} =: C_{O|M}(u_O | u_M)$$

where $C_{O|M}$ stands for the conditional copula. The conditional distribution, $C_{O|M}$ can be inverted and solved for u_O, for a given probability (of non-exceedance) $a \coloneqq C_{O|M}$ (e.g., a may express the 5, 50 or 95% uncertainty level). The above procedure can be compactly written as,

$$u_O^{a|u_M} = C_{O|M}^{-1}(a | u_M)$$

where, $C_{O|M}^{-1}(a|u_M)$ stands for the inverse of $C_{O|M}(u_O|u_M)$.

Copula-based modelling of predictive uncertainty [2]

Finally, in order to find $F^{-1}_{Y_O|Y_M}(a|y_M)$ the final step entails the transformation of $u_O^{a|u_M}$ from the uniform domain to the target one using the inverse CDF of its marginal distribution, i.e.,

$$y_{\mathrm{O}}^{a|u_{\mathrm{M}}} = F^{-1}_{Y_O|Y_M}(a|y_{\mathrm{M}}) = F^{-1}_{Y_O}\left(u_{\mathrm{O}}^{a|u_{\mathrm{M}}}\right) = F^{-1}_{Y_O}\left(C^{-1}_{\mathrm{O|M}}(a|u_{\mathrm{M}})\right)$$

or more compactly written as,

$$y_{\mathrm{O}}^{a|F_{Y_M}(\mathrm{y_M})} = F^{-1}_{Y_O}\left(C^{-1}_{\mathrm{O|M}}\left(a|F_{Y_M}(\mathrm{y_M})\right)\right)$$

As an example, for the Gaussian copula the latter expression reads as,

$$y_{\mathrm{O}}^{a|F_{Y_M}(\mathrm{y_M})} = F^{-1}_{Y_O}\left(\Phi\left(\theta\Phi^{-1}\left(F_{Y_M}(u_{\mathrm{M}})\right) + \sqrt{(1-\theta^2)}\Phi^{-1}(a)\right)\right)$$

where Φ denotes the univariate Gaussian CDF.

For the Clayton copula the above relationship reads as,

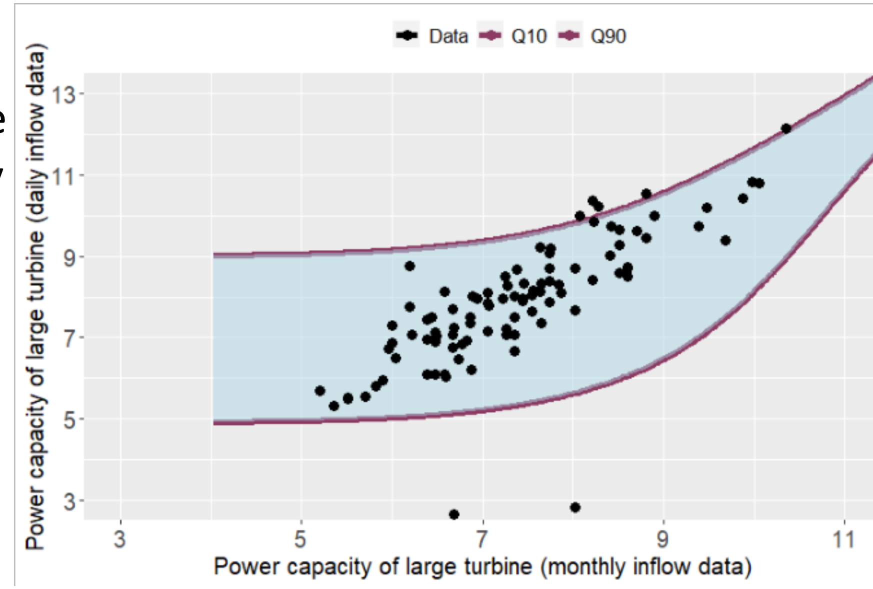
$$y_{\mathrm{O}}^{a|F_{Y_M}(\mathrm{y_M})} = F^{-1}_{Y_O}\left(\left(\left(a^{\frac{-\theta}{1+\theta}} - 1\right)F_{Y_M}(u_{\mathrm{M}})^{-\theta} + 1\right)^{-\frac{1}{\theta}}\right)$$

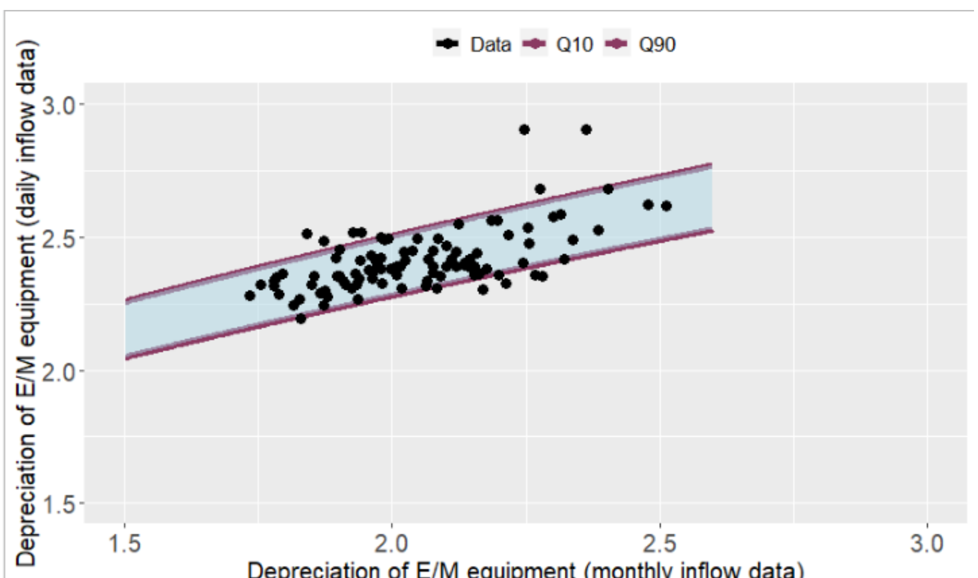
where θ denotes the copula parameter.

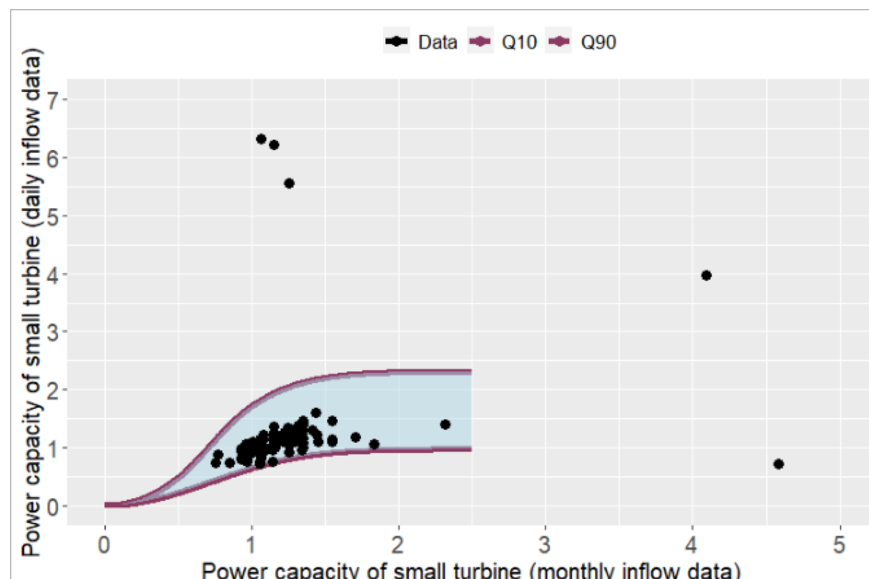
It remarked though that the top two relationships are general and hold for any other bivariate copula.

Uncertainty induced by time scale

- In the design of RoRs, the desirable resolution of inflow data is **daily**, although in practice many studies use **monthly** data. We repeat the design procedure using the standard efficiency curve, driven with **monthly stochastic inputs** that are generated by **aggregating** the original historical data.
- We quantify the process-scale uncertainty for the depreciation of the E/M equipment and the optimized power capacity of the two turbines.







Conclusions

- In small hydroelectricity, all key design quantities (turbine capacity, depreciation of E/M equipment, energy production) are subject to significant uncertainties induced by the **inflow data** and the **empirical efficiency curve** that are used in conventional sizing.
- As more **sources of uncertainty** are accounted for, the **variability** of the optimal system sizing is **amplified**.
- Our research indicated that the most vital sources of uncertainty are associated with:
  - the **temporal scale** and **size** of the inflow data sample;
  - the assumptions made about the **statistical distribution** of the inflow process and its **fitting** to the empirical data;
  - the selection of the efficiency curve and its systematic **degradation** over time.
- It is worth mentioning that the effects of uncertainty are not restricted to the design quantities *per se,* but also to the optimized operation policy, i.e. the **hierarchy within the turbine mixing.**
- The **uncertainty-aware design** approach, taking advantage of state-of-the-art **statistical, stochastic and copula-based tools**, makes a step from a unique optimal value "chained" to the limited information offered by empirical data, to a **cloud of optimal solutions**.
- This cloud provides the essential **decision-making framework** to select the design characteristics of the basis of **reliability**, expressed in terms of confidence intervals.

References

- Anagnostopoulos, J. S., and D. E. Papantonis, Optimal sizing of a run-of-river small hydropower plant, Energy Conversion and Management, 48(10), 2663-2670, doi:10.1016/j.enconman. 2007.04.016, 2007.
- Efstratiadis, A., Y. Dialynas, S. Kozanis, and D. Koutsoyiannis, A multivariate stochastic model for the generation of synthetic time series at multiple time scales reproducing long-term persistence, Environmental Modelling and Software, 62, 139–152, doi:10.1016/j.envsoft. 2014.08.017, 2014.
- **Sakki**, G.-K., I. Tsoukalas, and A. Efstratiadis, A reverse engineering approach across small hydropower plants: a hidden treasure of hydrological data?, Hydrological Sciences Journal, 2021 (under review).
- Sklar, M. Fonctions de repartition an dimensions et leurs marges. Publ. Inst. Stat. Univ. Paris 1959, 8, 229–231.
- Sklar, A. Random variables, joint distribution functions, and copulas. Kybernetika 1973, 9, 449–460
- Tsoukalas, I., P. Kossieris, and C. Makropoulos, Simulation of non-Gaussian correlated random variables, stochastic processes and random fields: Introducing the anySim R-Package for environmental applications and beyond, Water, 12(6), 1645, doi:10.3390/w12061645, 2020.