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Stochastic simulation-optimization framework for the design and assessment of renewable energy systems under uncertainty

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ABSTRACT

As the share of renewable energy resources rapidly increases in the electricity mix, the recognition, representation, quantification, and eventually interpretation of their uncertainties become important. In this vein, we propose a generic stochastic simulation-optimization framework tailored to renewable energy systems (RES), able to address multiple facets of uncertainty, external and internal. These involve the system's drivers (hydrometeorological inputs) and states (by means of fuel-to-energy conversion model parameters and energy market price), both expressed in probabilistic terms through a novel coupling of the triptych statistics, stochastics and copulas. Since the most widespread sources (wind, solar, hydro) exhibit several common characteristics, we first introduce the formulation of the overall modelling context under uncertainty, and then offer uncertainty quantification tools to put in practice the plethora of simulated outcomes and resulting performance metrics (investment costs, energy production, revenues). The proposed framework is applied to two indicative case studies, namely the design of a small hydropower plant (particularly, the optimal mixing of its hydro-turbines), and the long-term assessment of a planned wind power plant. Both cases reveal that the ignorance or underestimation of uncertainty may hide a significant perception about the actual operation and performance of RES. In contrast, the stochastic simulation-optimization context allows for assessing their technoeconomic effectiveness against a wide range of uncertainties, and as such provides a critical tool for decision making, towards the deployment of sustainable and financially viable RES.

1. Introduction

The EU has set a target of at least a 32% share of renewable energy in the final energy consumption by 2030. Yet today, energy production and consumption based on fossil fuels still represent more than 75% of the EU's greenhouse gas emissions, thus boosting EU members towards clean energy solutions. Two key objectives that we have been recently set by the European Commission for 2030, in the context of the running policy framework for climate and energy (also referred to as *Climate and Energy Framework 2030*) are: (a) an ambitious increase of energy efficiency up to 40%, regarding both primary and final energy consumption, and (b) further deployment of renewables, in order to exceed 40% in the final energy consumption in the EU. However, the systematically increasing penetration of renewable energy introduces further complexities to the global energy scene, due to multiple and interacting uncertainties [1,2]. This issue affects the entire life-cycle of renewable energy systems (RES), i.e., planning, design, policy management and operation [3,4].

As shown in Fig. 1, multiple sources of uncertainty exist, from the input "fuel" to its conversion to electricity production, and eventually the energy market. Their disentangling requires to separate them into exogenous (external) and endogenous (internal). The former category mainly refers to the inherent uncertainty of the system's drivers, i.e. hydrometeorological processes, also involving highly-complex and unpredictable socioeconomic and environmental factors, as well as conflicts within the broader energy-society nexus, e.g., land development [5]. On the other hand, internal uncertainties refer to conversion processes and underlying modelling assumptions.

The fact that renewable energy production is highly varying, intermittent and unpredictable across all scales, induces significant challenges to researchers and practitioners, in terms of successfully planning, scheduling, utilizing and controlling RES [6,7]. Nevertheless, it is recognized that the associated tasks, generally configured as optimization problems, can be effectively handled if uncertainties,

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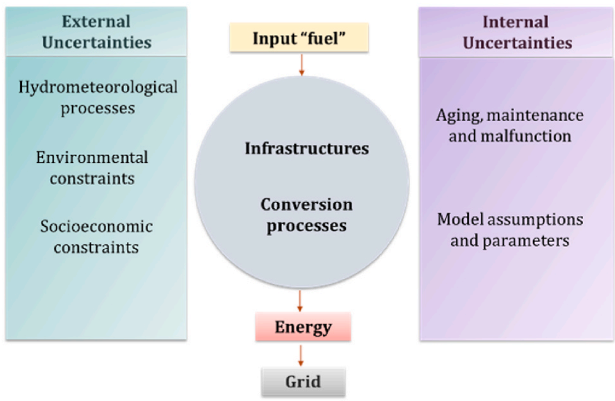

Fig. 1. Key sources of uncertainty associated with renewable energy.

probabilities, and fluctuating behaviors of renewable energy systems are properly represented [8].

This research highlights the importance of addressing the major facets of uncertainty, external and internal in combination, for two crucial life-cycle phases of RES, namely the technical design and the economic assessment. This problem is introduced in a generic simulation-optimization context, and then specified across the most popular types of RES, namely wind, photovoltaic and hydroelectric. The key objective is to formalize the endogenous and exogenous uncertainties across the input processes and model hypotheses, and eventually represent them under a novel uncertainty quantification framework, by coupling the methodological triptych of statistics, stochastics and copulas.

As a proof of concept for the effectiveness and generality of the proposed framework, we analyze two different cases. The first involves the design of a run-of-river small hydropower plant (SHPPs) in Achelous River basin, Western Greece, and particularly the estimation of the optimal mixing of its turbines. The underlying optimization problem aims to maximize the anticipated revenues from the long-term operation of the power plant, contrasted to the investment costs of the electromechanical equipment and the overall technical efficiency of the project, expressed in terms of capacity factor. The second case study refers to the long-term economic assessment of a planned wind power plant in the island of Ikaria (Greece). Both cases are handled through a modular scenario-based scheme, starting from the benchmark scenario, i.e., the conventional deterministic practice, and redounding to an integrated stochastic-probabilistic approach. This allows for capturing the key exogenous and endogenous uncertainties, and simultaneously providing decision support tools for design, strategic management, and evaluation of RES.

2. The challenges of RES under the uncertainty perspective

As mentioned, the design, assessment, management and operation of RES are subject to multiple uncertainties, spanning from their hydrometeorological drivers to storage, conversion, and power transfer cycles, including transmission capacity, generation availability, load requirements, unplanned outages, etc. [9]. Another crucial facet of uncertainty originates from the broader socioeconomic environment, thus being associated with governance, market rules, fuel and energy prices and market forces [10].

The different disciplines that are involved in RES address the issue of uncertainty from their own perspectives and methodological means. Environmental sciences have focused on capturing external uncertainties, and specifically those stemming from the highly varying nature of the input hydrometeorological processes. However, it is argued that this source of uncertainty is poorly only reflected when using short historical data within simulations [11]. In fact, these data may not be fully representative of the actual hydroclimatic regime of the process of interest, and cannot capture long-term changes, that are of key importance in the assessment of reliability and resilience of RES. A more comprehensive approach is offered by stochastic synthesis models that are able to reproduce the probabilistic behavior and dependence structure of the hydrometeorological process of interest across scales.

The use of stochastic models for generating long synthetic data, to be input to deterministic models, is a common practice in water resources and other environmental sciences [12]. The literature reports numerous modelling attempts for representing wind, solar and hydrological drivers through statistical and, less often, stochastic approaches [13–16]. The latter offer a consistent basis for process description, since they also account for dependencies in space, i.e. among correlated processes [17], and time. Mechanical and electrical engineering sciences have mainly explored internal uncertainties associated with the system properties (e.g., drop of efficiency due to ageing, maintenance and equipment malfunction), as well as model assumptions and parameters [18,19]. In general, such approaches refer to the microscale of the power machine, in order to capture facets of uncertainty across quite complex technical issues, e.g. pitch control to wind turbines [20].

However, the combined effects of internal and external uncertainties, as well as the interplay of their cascades and dependencies, have received considerably less attention to date [21], although it is accepted that the nonlinearities across the inflow-energy conversions usually amplify the overall uncertainty [22]. This leads inevitably to a fragmented approach in planning and management practices for RES, arguably impacting their performance, as quantified in terms of economy and reliability, and the emerging concept of resilience [23]. For instance, in the engineering context, conventional practices often ignore or, at least, underestimate these uncertainties and their dependencies. Yet, it is argued that the ignorance of uncertainty results into fully deterministic outcomes (i.e., a unique optimal design), which eventual leads to risky decisions, regarding critical technical quantities and the economic viability of RES.

In order to address this gap from a modelling perspective, three major research goals are arising, i.e.:

(a) The recognition of the multiple aspects of uncertainty, their dependencies (wherever applicable) and their importance across the life-cycle of renewables;
(b) The representation of uncertainties and their incorporation within a simulation-optimization context;
(c) The quantification and practical interpretation of the model outcomes under uncertainty.

In this vein, and since RES exhibit several common characteristics, a generic formulation of the simulation-optimization problem is introduced, accompanied by the associated principles for its configuration under a holistic uncertainty-aware framework. Herein are presented the overall theoretical background, followed by its specification across two common practical applications.

3. Simulation-optimization framework

3.1. Generic simulation model for RES

In contrast to power systems using fossil fuels, where energy production is predictable and controllable, in the case of RES the production follows the variability of the inflow source (wind, solar radiation, water). This variability can be mathematically described on the basis of statistical or stochastic terms, assuming a simulation context to link the power production, $\underline{p}$, with the hydrometeorological input, $\underline{x}$, which are both handled as random (better referred to as stochastic) processes (for convenience, throughout the text, we apply the underline notation to denote stochastic processes).

The transformation of the randomly varying input process, $\underline{x}$, to the output power, $\underline{p}$, is a nonlinear function which is generally expressed as:

$$\underline{p} = \begin{cases} 0 & x < x_{min} \\ \eta\left(\underline{x}\right) p_0\left(\underline{x}\right) & x_{min} \leq x < x_{max} \\ I & x_{max} \leq x < x_s \\ 0 & x \geq x_s \end{cases} \tag{1}$$

where $p_0\left(\underline{x}\right)$ is the theoretical power, I is the power capacity (also referred to as nominal power), and $\eta\left(\underline{x}\right)$ is the total efficiency, which are both driven by the stochastic process $\underline{x}$. The limits x_{min} and x_{max} are characteristics of the specific RES, while x_s represents a cut-out value, above which the machine stops for safety reasons.

The theoretical power depends on the location, layout and particular technical characteristics of the RES. In this respect, the theoretical wind power is given by:

$$p_0\left(\underline{v}\right) = \frac{1}{8}\rho_\alpha \pi D^2 \underline{v}^3 \tag{2}$$

where ρ_α is the air density, D is the diameter of the wind turbine and $\underline{v}$ is the wind velocity. Typical values of v_{min}, v_{max} and v_s are 3.0, 12.0 and 25.0 m/s, respectively.

For the common type of solar energy systems, namely the photovoltaic (PV) ones, the theoretical power is given by:

$$p_0\left(\underline{r}\right) = S\,\underline{r} \tag{3}$$

where S is the net area of photovoltaic panels and $\underline{r}$ is the incoming solar radiation. The operation of PVs is simpler than other RES, since their nominal power is by definition achieved at $r_{max} = 1000$ W/m^2.

Finally, the theoretical output power by a hydroelectric system is expressed in terms of hydrodynamic power:

$$p_0\left(\underline{h}, \underline{q_T}\right) = \rho\, g\, \underline{h}\, \underline{q_T} \tag{4}$$

where ρ is the water density, g is the gravity acceleration, $\underline{h}$ is the gross head, i.e., the elevation difference between the upstream water level and the outlet of the power station, and $\underline{q_T}$ is the flow passing through the turbines. Regarding the limits $q_{T,min}$, $q_{T,max}$ and $q_{T,s}$, these depend on the turbine characteristics, as further discussed in the first proof-of-concept study (section 4).

We underline that, in contrast to wind velocity and solar radiation, the turbine flow is not a purely natural process, but a spatiotemporal transformation (regulation) of the runoff produced over a catchment through a system of hydraulic works, employing diversion, storage, water transfer, etc. In this respect, the representation of the regulated process, $\underline{q_T}$, implies the use of an operation model of the associated water resource system, e.g., hydroelectric reservoir [24]. This model, symbolized, $\underline{q_T} = \Phi\left(\underline{q}\right)$, gets as input the "primary" stochastic process, by means of streamflow $\underline{q}$, and accounts for the constraints and decisions induced by the system's characteristics (e.g., reservoir and penstock capacity, storage-elevation relationship) and assigned management practices, respectively. Similarly, the gross head $\underline{h}$ derives from the operation model, since its variability is mainly dictated by the variability of the upstream reservoir level.

On the other hand, the total efficiency, $\eta\left(\underline{x}\right)$, is the product of individual efficiency values that refer to different components of the power transformation system, to express the associated energy losses. For instance, in the case of hydropower, this involves the hydraulic losses across the water conveyance system (penstock), the hydraulic, mechanical and mass losses in the turbines, as well as the power losses in the generator and the transformer. In general, these are subject to complex physical laws that make hard to establish accurate analytical expressions [25]. In this respect, each power machine has its own efficiency function, expressed by nomographs that are provided by the manufacturer, on the basis of laboratory results.

Characteristic examples for wind and hydro-turbines, as function of the associated input process, $\underline{x}$, are demonstrated in Fig. 2. It is interesting to remark that in all cases, the function $\eta\left(\underline{x}\right)$ is not monotonic. Nevertheless, the estimation of efficiency is subject to three key sources of uncertainty. The first is due to deviations between the actual performance of the power machine in the field and its prototype [26]. A characteristic example is the control of the pitch angle of wind turbines, which may significantly affect their real performance [27]. The second source of uncertainty originates from the drop of efficiency due to deterioration, damage and ageing of equipment over time. The last feature, which introduces further complexity and thus uncertainty, is the dependence of efficiency not only on the input, $\underline{x}$, but also on additional stochastic processes, such as the sediment transport causing erosion to hydro-turbines [28] or the temperature and other meteorological processes that affect the actual efficiency of PV panels [29].

3.2. The design optimization context

Herein we formalize the design optimization problem in multi-criteria terms, involving the estimation of a key characteristic of the RES, namely the determination of the total power capacity and its sharing to its individual components. In this respect, we consider a given layout of the system, such as a wind park, a solar park or a hydroelectric station, where the siting of all supporting infrastructures, by means of

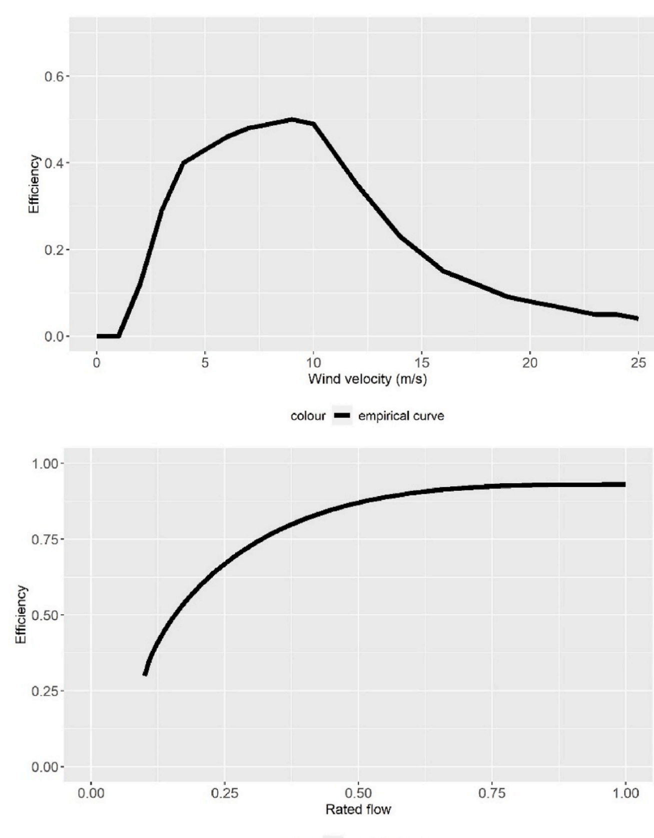

Fig. 2. Examples of efficiency functions for a wind turbine (up) and a Pelton-type turbine (down).

civil works (e.g., power station house, road network), are already specified. We remark that the design of most of civil infrastructures is strongly related the power capacity of the overall system and its individual components. In this vein, the design variables to optimize are expressed as a vector $\boldsymbol{I} = [I_1, I_2, \ldots, I_{NS}]$, where NS is the number of the system's components.

The standard technoeconomic optimization problem is formalized as the maximization of financial quantities, such as the net present value (NPV). According to this concept, the discounted value of future net cash flows should exceed the investment cost, so as to ensure a sustainable investment [30]. In our case, the cash flows derive from the production of electrical energy during the entire life-cycle of the system, while the investment cost, involving the electromechanical (E/M) equipment and the civil works, is directly or indirectly associated with the power capacity.

Following this, by considering a financial period of n years with a specific interest rate i, the equivalent annual cost of the investment is given by:

$$A = C\,\frac{i\,(1+i)^n}{(1+i)^n - 1} \tag{5}$$

where C is the total investment cost, which is the sum of individual costs, C_i. All these costs are subject to the key principle of economy of scale, thus expressed as:

$$C_i = f\left(I_i^{\lambda}\right) \tag{6}$$

where $\lambda < 1$ is a shape parameter, expressing the reduction of unit cost with respect to power capacity.

In order to implement the aforementioned cash-flow method in a risk-aware context, the expression of future revenues should be determined in terms of mean annual energy production, $E_a = \mathrm{E}\left[\underline{p}\right] T_a$ (where T_a denotes the annual duration), multiplied by a unit price, $\underline{u}$. The estimation of power production requires running a simulation model, thus E_a is actually a stochastic variable. In addition, the unit price $\underline{u}$ can also generally be considered as a stochastic process [31], since it varies in the context of free electricity market trade and supply. Under this premise, the objective function of the design optimization problem is expressed in annual profit terms as:

$$F\left(\boldsymbol{I},\,\underline{p}\right) = \underline{u}\,E_a\left(\boldsymbol{I},\,\underline{p}\right) - A(\boldsymbol{I}) \tag{7}$$

This function is strongly nonlinear and contains two conflicting components, namely the mean annual energy production, $E_a\left(\boldsymbol{I},\,\underline{p}\right)$, to maximize, and the equivalent annual cost, $A(\boldsymbol{I})$, to minimize.

To ensure robust solutions, in the multicriteria optimization problem we also embed a third component, which is the resulting capacity factor, CF, of the system under study. According to its common definition, CF is expressed as the ratio of the mean annual electrical energy output to the maximum possible one [32], i.e.:

$$CF\left(\boldsymbol{I},\,\underline{p}\right) = \frac{E_a\left(\boldsymbol{I},\,\underline{p}\right)}{T_a \sum_{i=1}^{N} I_i} \tag{8}$$

where T_a is the annual duration.

Although CF seems being a rather technical quantity, it is actually a fundamental performance metric of power systems, thus its interpretation plays key role in the evaluation of the viability of a RES. In particular, a low CF is not necessarily associated with poor performance in terms of energy production, but may also be due to the application of a too large installed capacity that is activated a small portion of time.

Since the other two criteria are given in monetary terms, the incorporation of CF within the generic optimization problem is made by assigning a penalty term, to achieve CF values over or close to a desirable threshold, CF^*. The latter is site-specific and varies across different RES types [33]. Under this premise, the proposed multi-objective function to maximize is written as:

$$F'\left(\boldsymbol{I},\,\underline{p}\right) = F\left(\boldsymbol{I},\,\underline{p}\right) - \max\left[0,\; CF\left(\boldsymbol{I},\,\underline{p}\right) - CF^*\right] w \tag{9}$$

where w is a suitable weighting coefficient.

3.3. The triptych of statistics, stochastics and copulas in practice

As shown in Fig. 3, the proposed modelling framework under uncertainty follows the Monte Carlo paradigm, which makes use of three tools from the broader probability theory, i.e., stochastics, statistics, and copulas. The first two aim at capturing the major aspects of uncertainty that originate from the inherently random input processes and the model hypotheses, while copulas are used in the post analysis phase, as explained herein.

The Monte Carlo approach is applied to the simulation model, which involves most of practical issues of renewable energy (planning, design, long-term assessment, short-term control, etc.). This is configured by means of equally probable simulation scenarios that correspond to m different system's states and input processes. Each hypothetical state runs for N years, which equals the economic life of the project of interest. The state is expressed through two key characteristic properties, namely the efficiency function $\eta\left(\underline{x}\right)$ and the unit price, $\underline{u}$. The first is associated with the internal operation of the RES per se, while the second derives from the uncertain socioeconomic environment. In particular, the formulation of efficiency under uncertainty presupposes to introduce an analytical formula, symbolized $\eta\left(\underline{x}, \underline{\boldsymbol{\psi}}\right)$, for the associated machine, where $\underline{\boldsymbol{\psi}}$ is a set of parameters that describe the shape of the curve. These are also represented as random variables, in order to capture all possible fluctuations from the standard commercial curve. This issue is further discussed in the two case studies, providing probabilistic parametric formulas for the power conversion curves of hydro and wind turbines, respectively.

Under this premise, the Monte Carlo scenarios are configured by assigning appropriate distribution functions to $\underline{\boldsymbol{\psi}}$ and $\underline{u}$ and then employing random sampling to define the m potential states of the system. Furthermore, in order to express the external uncertainties induced by the local hydrometeorological regime, each scenario is driven with long synthetic data of length N for the corresponding input processes $\underline{x}$. In this respect, a stochastic model is applied to generate $m \times N$ years of synthetic data, and this sample is then split into m sub-sets, also referred to as ensembles. The temporal resolution of the data depends on the specific process (e.g., hourly for wind velocity and solar radiation, daily for streamflow).

Consequently, outcomes of the simulation scenarios are m ensembles of output processes (e.g., power production) and associated design components (e.g., optimized power capacity) and performance assessment metrics (e.g., mean annual revenues, capacity factor). In this vein, all outputs are represented in stochastic terms, which also allows for quantifying their uncertainty through statistical analyses of the corresponding simulated data. For instance, we can fit suitable probability density functions (pdfs) to individual design and performance assessment metrics. Further insight can be provided by accounting for the joint uncertainty induced by cross-dependencies between the derived design variables and performance metrics. The underlying methodology is based on the work of Tsoukalas [34], and relies on the use of (Gaussian) copulas to establish the conditional distribution of two (non-Gaussian) random variables. A summary of the employed method is provided in Appendix A.

The generic algorithmic procedure for the design case, which also

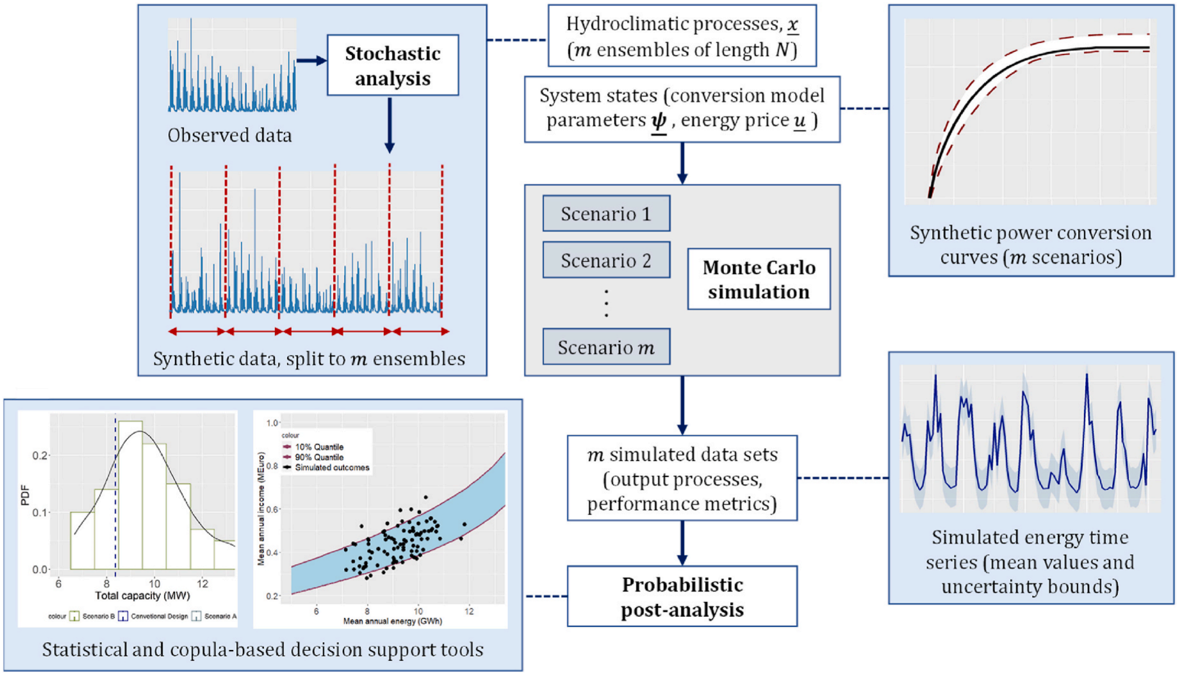

Fig. 3. Schematic layout of the proposed framework.

contains the assessment problem, is depicted in Fig. 4. The application of the aforementioned framework is demonstrated by means of two (simplified) proofs-of-concept, where a modular approach is adopted, thus adding progressively more sources of uncertainty within simulation and optimization.

4. Proof of concept A: optimal design of run-off-river hydroelectric plant under uncertainty

4.1. Key principles of hydropower system operation

The uncertainty-aware framework, in the design context, is stressed for a run-off-river (RoR) small hydropower plant, which is a quite complex and promising renewable source. This type of hydroelectric system diverts part of the streamflow arriving to an intake structure, located in the riverbed, to a forebay tanks and then to the power station, which is generally located far from the intake, to create a significant elevation difference.

For a given layout, the design problem lies in the selection of an optimal mixing of turbines, in order to capture as much as possible of the streamflow variability. Let consider a RoR plant comprising two turbines of power capacity, I_1 and I_2, operating within flow ranges ($q_{1,min}$, $q_{1,max}$) and ($q_{2,min}$, $q_{2,max}$), respectively. The range of operation of each turbine is determined by its power capacity. In particular, the maximum discharge is given by:

$$q_{i,max} = \frac{I_i}{\rho\ g\ \eta_{i,max}\ h_n} \tag{10}$$

where $\eta_{i,max}$ is the total efficiency of the electromechanical equipment, and h_n is the net head, i.e., the difference between the gross head and the hydraulic losses across the water conveyance system. These losses can be analytically estimated, on the basis of discharge, diameter and other properties. On the other hand, the minimum operational discharge is simply expressed as portion of the maximum one, i.e., $q_{i,min} = \theta\ q_{i,max}$, where θ depends on the turbine type.

Summary of algorithmic procedure for the design of RES under uncertainty

Step 1: Generation of $m \times N$ years of synthetic driving data (e.g., streamflow, wind velocity, solar radiation) at the appropriate temporal resolution (N: project lifetime).

Step 2: Generation of m equally probable system states (e.g., power curves, energy price)

Step 3: Formulation of m Monte Carlo simulation scenarios by splitting synthetic drivers into m ensembles of N-year length and by sampling random system states from the corresponding set

Step 4: Set up of the optimization procedure (*design variables*: power capacity values of system's components, *objective function* as formalized in eq. 9)

Step 5: Extraction of m optimized design variables and associated performance metrics

Step 6: Statistical processing of simulation-optimization outcomes:

- Marginal analysis by fitting probability density functions
- Dependence analysis through copulas

Step 7: Selection of final design quantities accounting for their uncertainty

Fig. 4. Logical flow of the proposed framework regarding the design optimization problem.

The mixed scheme operates from the minimum flow between $q_{1,min}$ and $q_{2,min}$, and the sum $q_{1,max} + q_{2,max}$. A typical operation policy implies the use of the large turbine in priority, while the small one receives the surplus flow, up to its capacity [35]. In some cases, a safety limit, q_s, is also imposed, to interrupt the operation of turbines during significant flood events [36]. Finally, the turbine efficiency can be expressed through the following parametric formula, introduced by Sakki et al. [37]:

$$n = n_{min} + \left(1 - \left(1 - \left(\frac{q^* - \theta}{1 - \theta}\right)^a\right)^b\right)(n_{max} - n_{min}) \tag{11}$$

where $q^* = q_T/q_{max}$ is the rated flow, n_{min} and n_{max} are the upper and lower efficiency values, and a and b are shape parameters depending on the turbine type. The total E/M efficiency is obtained by multiplying with an adjusting factor, with typical value 0.95.

4.2. Study area, data and design assumptions

The hydropower plant under design is established in a sub-catchment of Achelous River in Western Greece, taking advantage of a gross head of 150 m. The penstock length and diameter are 500 m and 1.5 m, respectively. The available historical data comprises daily streamflow records for 39 years, with mean annual value 2.15 m^3/s [38]. Following the Greek legislation, we apply an environmental flow to be released downstream of the intake, which equals to 0.25 m^3/s.

The key design objective involves the setting of two Francis-type turbines. Their efficiency is approximated by eq. (11), where $n_{min} = 0.30$, $n_{max} = 0.93$, $a = 0.80$ and $b = 3.75$. For the estimation of hydraulic losses across the penstock, we consider a roughness coefficient up to 1.0 mm.

4.3. Deterministic optimization context

Since the configuration of the major system components (intake and power station sites, layout of diversion, penstock diameter) are already specified, their investment costs are fixed. In this respect, the annual profit component (eq. (5)) includes the cost of E/M equipment, which implies a high percentage (30–40%) of the total budget of a typical small hydropower plant [39]. In the literature, this cost is linked with the power capacity, I, and the gross head, h, through empirical relationships. In the present study we apply the following formula, proposed by Aggidis et al. [40]:

$$C = C_0\, I^{\alpha}\, h^{\beta} \tag{12}$$

where $C_0 = 14\,400$ €, $\alpha = 0.56$ and $\beta = -0.112$.

The rest assumptions for the configuration of the objective function (eq. (9)) involve the assignment of selling price of electrical energy and the capacity factor threshold, which are set equal to $u = 0.087$ €/kWh and $CF^* = 0.25$, respectively. We remark that, although this price should, in general, be handled as a random variable, here we employ a fixed value, according to the Greek legislation for small hydroelectric plants that are not yet entered the energy market model. On the other hand, the selection of CF^* is based on engineering evidence, and prohibits the derivation of oversized turbines, in order to exploit large yet low-frequency streamflows.

To insight to the optimization problem, we repeat the design procedure for a large number of turbine capacity combinations, driven with the historical streamflow data. We highlight that since the formulation of the problem is deterministic, it leads to a unique solution, i.e., the global optimum of the profit function. Interestingly, as shown in Fig. 5, the response surface comprises two regions of attraction, and thus two optimal mixings, with quite close performance. These reveal two alternative operation policies, one by setting in high priority the large turbine (global optimum) and the other the small one (local optimum).

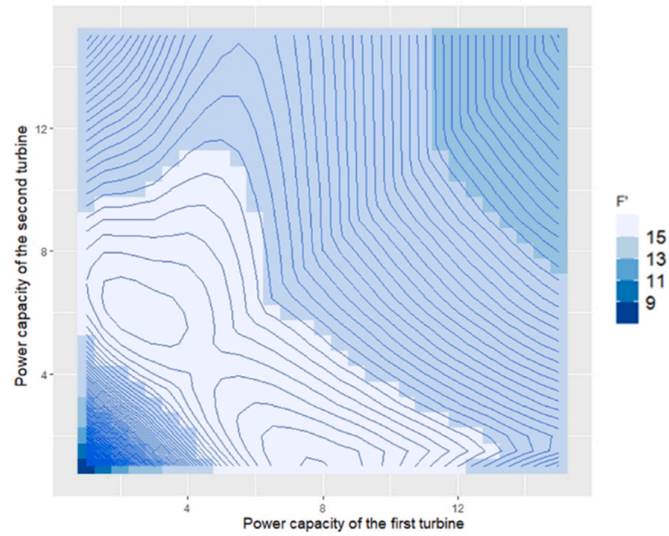

Fig. 5. Response surface of the profit function, highlighting the two optima points that indicate alternative turbine mixings.

4.4. Building the design procedure under uncertainty

In order to better reveal the potentials of the stochastic design framework over the conventional, deterministic one, we demonstrate the modular scheme to disentangle the key sources of uncertainty, external and internal. In particular, we establish three settings of the optimization problem under uncertainty, herein symbolized A, B and C.

The two first settings aim to represent the external uncertainty, originating from the natural variability of streamflow. In this respect, we provide 100 ensembles of synthetic daily streamflow data, each one covering a 20-year horizon (i.e., the economic life of small hydropower plants, according to the Greek legislation), to drive the optimization procedure. In particular, setting A consists a pure statistical approach, where 100 × 20 years of daily synthetic data are sampled from a Generalized Gamma distribution model. This procedure maintains the overall probabilistic structure of the daily streamflow, yet it ignores major features of hydrological processes, such as seasonality and dependencies across scales. Besides, setting B is more complete, since it is based on the stochastic approach for data generation. In this respect, we employ the anySim package [41], which is suitable for simulating processes of any distribution and dependence structure across multiple temporal scales. Specifically, anySim is used to generate synthetic data that reproduce the stochastic regime of the observed streamflow across seasons and across three scales of interest (daily, monthly, annual).

The more integrated setting C augments the above-mentioned setting, by embedding a major source of internal uncertainty, i.e., the turbine efficiency. In this vein, we repeat the 100 optimization scenarios, driven with synthetic streamflow data and with equally probable efficiency formulas (Fig. 6). Following the rationale of section 3.3, we consider the four parameters of eq. (11) as random variables, thus we sample the efficiency bounds η_{min} and η_{max} from a Beta distribution, and the shape parameters a and b from a Normal one. This ensures that the derived curves are asymmetrically spread around the standard one, to account for the effects of systematic drop of efficiency due to ageing.

4.5. Results

Each optimization setting results to scenarios of 100 equally probable optimized sets of power capacity values and associated performance metrics. As shown in Fig. 7, the uncertainty-aware design procedure leads to two characteristic patterns across the two regions of attraction, already revealed from the deterministic optimization

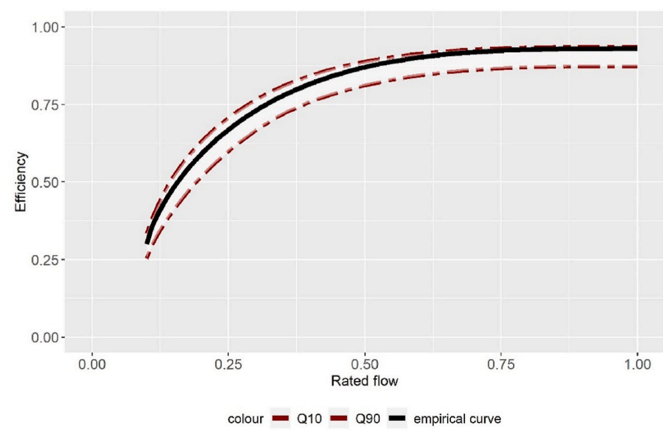

Fig. 6. Equally probable efficiency curves asymmetrically spread around the standard (empirical) one to emphasize aging effects.

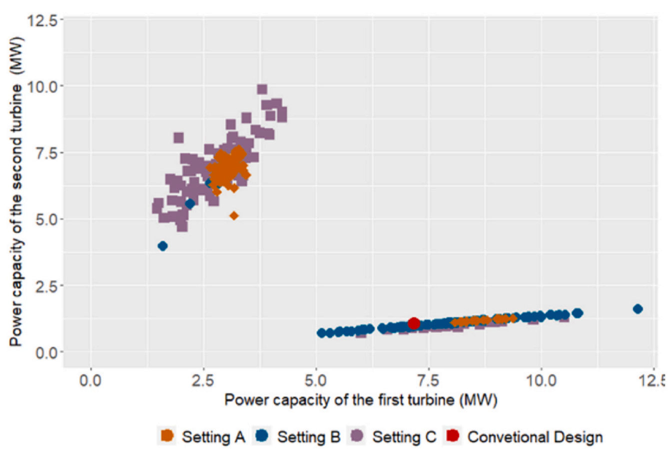

Fig. 7. Optimized sets of turbine mixing for the three problem settings.

approach. The lower right pattern, which implies the use of the larger turbine as primary, is well-approximated by a linear relationship, while the upper left one formulates an oval scheme. We highlight that as the description of uncertainty becomes more detailed, the spread of these patterns increases, and, furthermore, their distribution is the objective space changes significantly. As shown in Table 1, the incorporation of uncertainty leads to a wide range of optimal values across all key quantities of the design procedure (total capacity, investment costs, etc.). As expected, these differ across the alternative settings.

In Fig. 8, we fit a probability density function (pdf) to the ensemble of optimized total capacity values (for setting C, accounting for both external and internal uncertainties) and contrast it with the single value provided by the deterministic approach. Furthermore, in Fig. 9, we apply the copula theory, in order to quantify the predictive uncertainty of the anticipated profits against the total power capacity. In a real-world practice, the user can first refer to Fig. 8 for turbine sizing, by selecting an appropriate quantile (which represents the risk of the design policy), and next take advantage of Fig. 9, in order to quantify the predictive uncertainty of the investment.

Table 1
Summary of results from the alternative design approaches.

Design approach	Deterministic	Setting A	Setting B	Setting C
Total capacity (MW)	9.9	8.3–11.0	5.6–13.8	6.7–13.7
Investment cost (10^6 €)	3.4	3.0–3.8	2.2–4.4	2.4–4.6
Mean annual energy (GWh)	16.2	17.0–19.0	12.0–25.0	11.4–24.0
Capacity factor	0.25	0.22–0.33	0.19–0.25	0.18–0.24

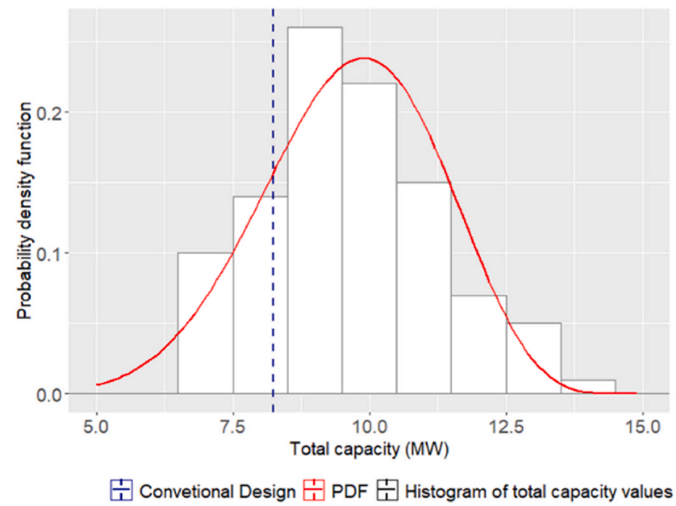

Fig. 8. Fitting of Beta distribution to the set of optimized total capacity values (setting C).

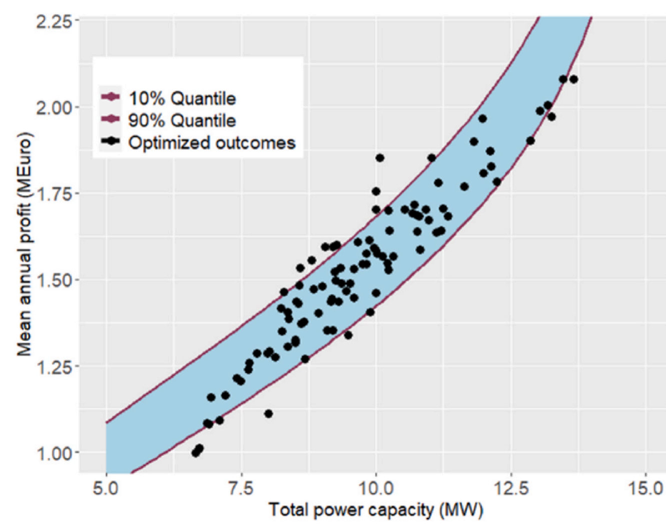

Fig. 9. Fitting of Gaussian copula to total power capacity and mean annual profit (setting C).

5. Proof of concept B: long-term assessment of a wind turbine system performance

The second case study seeks for the long-term assessment of a wind power park, by accounting for its main internal and external uncertainties. This is established in a small Aegean island (Ikaria, Greece), and consists of two turbines with different power capacity, i.e., 1.0 MW and 2.3 MW, different hub heights, i.e., 59 and 85 m, respectively, and thus different power curves. These curves are also expressed by the parametric formula of eq. (11), where the streamflow is replaced by wind velocity and thus $v^* = v_T/v_{max}$ is the rated wind velocity, n_{min} and n_{max} are the upper and lower efficiency values, and a and b are the shape parameters. The two curves are demonstrated in Fig. 10.

The turbines are established in-line and aligned with the prevailing wind direction. Since the large turbine is upstream, for the energy production we account for the interaction (e.g., due to turbulence effects) between them, by decreasing the wind velocity to the second turbine as follows [42]:

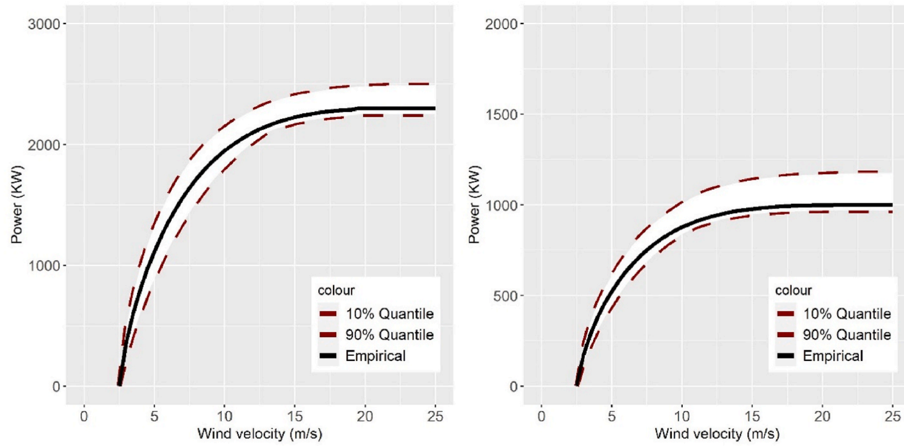

Fig. 10. Fitting of power curves to the original prototype for the two wind turbines and associated uncertainty bounds.

$$v = v_o \left(1 - \frac{2a}{\left(1 + 2\,k\,L/D_L\right)^2} \right) \tag{13}$$

where v_o is the freestream wind velocity at the hub height level, k is the decay coefficient, and a is the induction factor. Here, for the decay coefficient and the induction factor we are applying the values proposed by Vasel-Be-Hagh and Archer [42], i.e., $k = 0.038$ and $a = 0.10$. Following this, L is the distance between the two wind turbines and D_L is the diameter of the large turbine, which are equal to 400 m and 71 m, respectively.

The assessment procedure follows the same practice with the design proof of concept, thus expressing the internal and external uncertainties into three settings. As before, the first two aim at representing the external uncertainty, by providing 100 ensembles of synthetic hourly wind velocity with 25 years length (i.e., the lifetime of the project). We remind that the first setting ignores the dependencies across scales and the effects of seasonality, while the second setting reproduces the full regime of the observed wind velocities, as demonstrated in Fig. 11. The last setting combines the internal and external uncertainties, by enhancing the second setting with a more detailed approach for the turbine power curve. Specifically, 100 equally probable power curves for the two wind turbines are formulated, in order to express the uncertainty that reveals in their real operation. As shown in Fig. 10, the uncertainty bounds are negative asymmetrically spread, in order to reflect the observed deviation between the manufacturer's power curve and the output power at the site [43]. For all settings, the economic performance of the wind power plant is expressed in stochastic terms, by applying a randomly varying energy price, which reproduces the statistical characteristics of the historical timeseries for a 5-year period (2015–2020). As made with the wind velocity process, 100 ensembles of hourly price timeseries for the 25-year period of simulation are generated, via the anySim package. The timeseries of the actual price data and one out of 100 synthetic samples are illustrated in Fig. 12.

Each simulation results to 100 scenarios of characteristic quantities of interest for assessing the vitality of the RES, e.g., mean annual energy, expected profit, etc. A summary of the key outcomes is demonstrated in Table 2. In order to quantify the predictive uncertainty of the mean annual income, a copula model if fitted with respect to mean annual energy, as demonstrated in Fig. 13. The practical use of this graph is discussed in next section.

6. Discussion: implication for energy planners, managers and stakeholders

Our analyses indicated that the proper representation of uncertainty is not just a "game for statisticians", but has a significant operational relevance. Besides the pure technical sector, the proposed uncertainty-aware framework involves multiple groups of interest, from energy planners and managers to policy-makers and stakeholders.

From a technical point-of-view, it provides a holistic route to the design and economic assessment of RES, by representing their potential real-world operation through Monte Carlo scenarios. This is a major step forward the running paradigm, hypothesizing a unique future state of the system, under known internal and external conditions (i.e., forcing

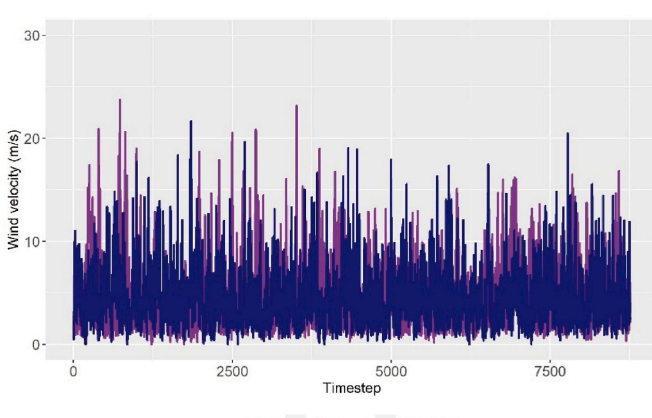

Fig. 11. Stochastic and observed wind velocity data (randomly selected window of one year length).

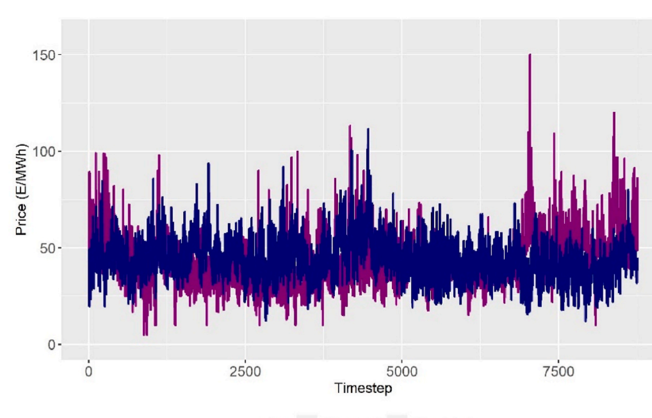

Fig. 12. Stochastic and observed price data (randomly selected window of one year length).

Table 2
Summary of results from the alternative assessment approaches.

Assessment approach	Deterministic	Setting A	Setting B	Setting C
Mean annual energy (GWh)	8.97	9.19	9.13	9.19
Minimum annual energy (GWh)	–	9.13	6.96	7.02
Maximum annual energy (GWh)	–	9.25	11.11	11.40
Mean annual income (10^6 €)	0.36	0.38–0.53	0.18–0.63	0.37–0.66

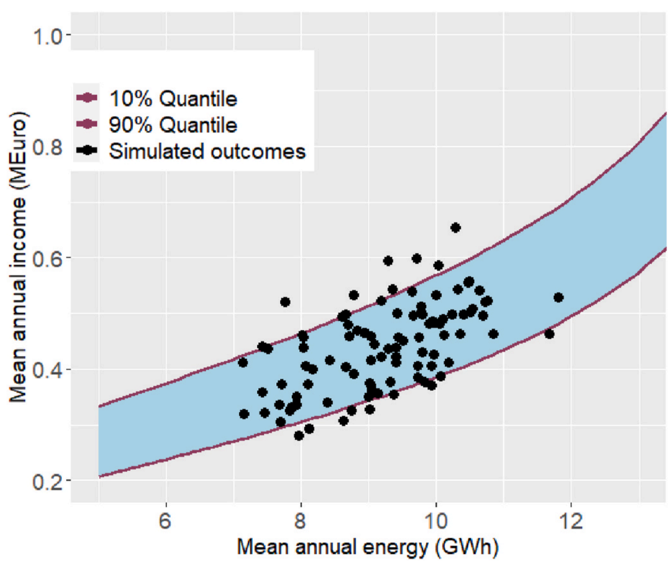

Fig. 13. Fitting of Gaussian copula to mean annual energy and mean annual income (setting C).

processes and characteristic properties). The resulting shift from the unique deterministic solution to the ensemble of possible options allows for interpreting the outputs of simulation and optimization in probabilistic terms. Overall, this approach can be the means to estimate the combined risks derived from the multiple sources of uncertainty and thus assist in the decision level. For instance, in the design of small hydroelectric plants, the coupling of Figs. 8 and 9 offers a decision tool for selecting the optimal turbine mixing and quantifying the full range of uncertainty with respect to anticipated performance of the system.

The embedding of uncertainties can also be incorporated in the evaluation of renewable energy systems at a more macroscopic level. This approach has a twofold value a) for planned projects, it reveals a priori their vitality, and b) for existing systems, it highlights their potential weaknesses. For instance, the graph shown in Fig. 13 can be used as a strategic management tool for both potential and existing projects. Specifically, in the case of existing projects with already known performance, in terms of mean energy production, we can estimate the anticipated range of associated profits, and thus recognizing whether the system is effective or not. In addition, in the planning context regarding the deployment of potential RES, the stochastic simulation procedure offers a priori the valuable information about not only the mean annual energy per se but also the expected revenues from their long-term operation.

The abstract information and knowledge gained from the aforementioned procedure can be eventually served as a communication channel with investors, stakeholders and local communities, which are the actual beneficiaries from a proper design and effective operation and management of RES.

7. Conclusions

An accurate representation of uncertainties is crucial across all aspects of renewable energy. This research presents and discusses the principles of a holistic simulation-optimization approach for such systems, by first recognizing the key sources of uncertainty, external and internal, and by setting them within a probabilistic framework. In this respect, the representation of uncertainties is made through the probabilistic triptych: (a) statistics, accounting for marginal properties of independent variables, (b) stochastics, also accounting for dependencies of hydrometeorological drivers, and (c) copulas, for quantifying the joint uncertainty of simulated outcomes. As the three most widespread RES (wind, solar, hydroelectric) have fundamental similarities, a generic procedure for the related design and long-term performance assessment problems is established, which is a significant novelty of this work.

In the proposed framework, all uncertain components within the design and the long-term assessment of RES are expressed in probabilistic terms, either as stochastic processes or randomly varying quantities (i.e., model parameters). Particularly, the representation of internal uncertainties across the energy conversion phases is simply made by introducing parametric analytical formulas for the system's efficiency and sample their parameters from suitable distribution models. This is a key methodological novelty, which also avoids the application of detailed physical models for capturing complex uncertainties at the microscale. The combined effects of internal and external uncertainties are finally mapped to the outputs of interest, namely the optimized design variables (i.e., power capacity values) and the key performance assessment metrics (i.e., investment costs, expected energy production and revenues, capacity factor). In the context of their post-analyses, we have also developed probabilistic tools, also based on copulas, for quantifying individual and joint uncertainties.

The modular application of the uncertainty-aware framework to the design of a small hydroelectric plant as well as to the assessment of a planned wind power park, revealed significant benefits of the proposed approach over conventional deterministic practices. Specifically, the contrast between settings A and B confirmed that ignoring seasonality and dependence effects within the simulation of the input processes (here, streamflow and wind velocity) hides a substantial part of uncertainty. Furthermore, the incorporation of internal uncertainties (setting C) ensured a more holistic viewpoint, since it allowed for representing the deviations of theoretical conversion models from the actual performance in the field. Within the design problem, this approach favored, for example, a different hierarchy in the turbine mixing.

As a conclusive remark, also derived from the discussion of section 6, is that the coupling of uncertainty in the assessment of RES, either existing or planned, also has a practical footprint. In fact, it is crucial for the evaluation of the system's performance under alternative states (hydroclimatic and economic drivers, as well as operational conditions) and the quantification of associated risks. The explicit incorporation of the concept of risk within RES design and planning, which has been the overall outcome of this research, allows decision makers and stakeholders to assess, a priori, whether the investment is effective and sustainable.

Ongoing research is focused on the highly unpredictable social factor, which has multiple synergies and interactions with renewable energy, thus handling the overall problem from the perspective of socio-technical system under uncertainty.

Credit author statement

Georgia Konstantina Sakki: Conceptualization, Investigation, Formal analysis, Methodology, Software, Writing - Original Draft, Writing - Review & Editing; Ioannis Tsoukalas: Methodology, Software, Formal analysis, Writing - Original Draft; Panagiotis Kossieris: Software, Formal analysis; Christos Makropoulos: Supervision, Funding acquisition; Andreas Efstratiadis: Conceptualization, Methodology, Writing -

Original Draft, Writing - Review & Editing, Supervision

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Copula theory [44] enables the construction of multivariate joint distributions with arbitrary marginals. Due to this flexibility, nowadays the use of copulas have been popularized in a variety of scientific domains [45], including renewable energy [46,47]. Such constructs can also be used for the establishment of conditional distributions which are very often of interest (i.e., estimate the distribution of the random variable Y given that we have observed a realization x of the random variable X). To elaborate, let us focus on the case of the Gaussian copula and its use for the construction of non-Gaussian conditional distributions, based on the method by Tsoukalas [34]. Let X and Y denote two random variables (RVs), while $F_X(x)$ and $F_Y(y)$ stand for their cumulative distribution functions (cdf). According to copulas, their joint cdf can be expressed by,

$$F(x,y) = P\{X \le x, Y \le y\} = C(F_X(x), F_Y(y)) = C(u_X, u_Y) \tag{A.1}$$

where $C(\cdot,\cdot)$ denotes the copula cdf, as well as $u_X = F_X(x)$ and $u_Y = F_Y(y)$ are uniformly distributed in [0, 1]. For the case of the Gaussian copula, the latter reads as follows:

$$C(u_X,\ u_Y) = \Phi_2\left(\Phi^{-1}(u_X), \Phi^{-1}(u_Y); \theta\right) \tag{A.2}$$

where Φ_2 and Φ stand for the bivariate and univariate Gaussian cdf respectively, while $\theta \in [-1, 1]$ denotes the copula parameter, which is linked, yet not necessarily equal, to the correlation coefficient of X and Y, since it depends on their marginals – see discussion in Tsoukalas et al. [48]. The conditional cdf of the RV $X|Y = y$, that is $F_{X|Y=y}(x) = P\{X \le x|Y = y\}$ can be obtained through the following relationship:

$$F_{X|Y=y}(x) = \frac{\partial C(u_X, u_Y)}{\partial u_Y} := C_{X|Y}(u_X|u_Y) \tag{A.3}$$

where $C_{X|Y}$ stands for the so-called conditional copula. For the case of the Gaussian copula, the latter relationship reads as follows:

$$a := F_{X|Y=y}(x) = C_{X|Y}(u_X|\ u_Y) = \Phi\left(\frac{\Phi^{-1}(u_X) - \theta\Phi^{-1}(u_Y)}{\sqrt{(1-\theta^2)}}\right) \tag{A.4}$$

which can be inverted to:

$$u_X^{a|u_Y} := C_{X|Y}^{-1}(a|\ u_Y) = \Phi\left(\theta\Phi^{-1}(u_Y) + \sqrt{(1-\theta^2)}\,\Phi^{-1}(a)\right) \tag{A.5}$$

in order to find the value of u_X that corresponds to a desired probability of non-exceedance $a := C_{X|Y}$ given the (known) value of u_Y (compactly written as $u_X^{a|u_Y}$). Finally, one can also obtain the quantile that corresponds to that conditional probability level by employing the inverse cdf of X, i.e., $F_X^{-1}(\cdot)$. The latter reads:

$$x^{a|F_Y(y)} = x^{a|u_Y} = F_X^{-1}\left(u_X^{a|u_Y}\right) \tag{A.6}$$

while for the Gaussian copula case it only entails a substitution of Eq. A.5 to A.6.

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Nomenclature

Symbol Description

$\underline{p}$: Power production
$\underline{x}$: Hydrometeorological input process
$p_0\left(\underline{x}\right)$: Theoretical power
I: Power capacity
$\eta\left(\underline{x}\right)$: Total efficiency
x_{min}: Cut-in value of input process
x_{max}: Characteristic value of input process to achieve the power capacity
x_s: Cut-out value of input process
ρ_a: Air density (1.225 kg/m^3)
D: Diameter of wind turbine's rotor
$\underline{v}$: Wind velocity process
S: Net area of photovoltaic panels
$\underline{r}$: Solar radiation process
ρ: Water density (1000 kg/m^3)
g: Gravity acceleration (9.81 m/s^2)
$\underline{h}$: Gross head
$\underline{q_T}$: Flow passing through the hydro-turbines
$\Phi\left(\underline{q}\right)$: Regulation function applied to streamflow process
NS: Number of system's components
n: Depreciation period (years)
i: Interest rate
A: Equivalent annual cost of the investment
C: Total investment cost
C_i: Individual cost
λ: Shape parameter of generic cost function
E_a: Mean annual energy
T_a: Annual duration (8760 h)
$\underline{u}$: Unit price of energy sell
$F\left(\boldsymbol{I}, \underline{p}\right)$: Objective function of the design optimization problem
CF: Capacity factor
CF^*: Desirable threshold for CF value
$F'\left(\boldsymbol{I}, \underline{p}\right)$: Multi-objective function of the design optimization problem

w: Weighting coefficient
$\eta\left(\underline{x},\underline{\psi}\right)$: Analytical formula for the efficiency curve
$\underline{\psi}$: Set of parameters describing the empirical efficiency curve
m: Number of scenarios within Monte Carlo simulation
h_n: Net head
θ: Ratio of minimum to maximum turbine flow
q^*: Rated flow (dimensionless)
a, b: Shape parameters of analytical efficiency formula
$C_0, \alpha\ \beta$: Parameters of electromechanical equipment cost function
v_o: Freestream wind velocity at the hub height level
k: Decay coefficient
a: Induction factor
L: Distance between adjacent wind turbines
D_{max}: Diameter of the largest wind turbine's rotor