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Levelized cost of electricity in renewable energy communities: Uncertainty propagation analysis

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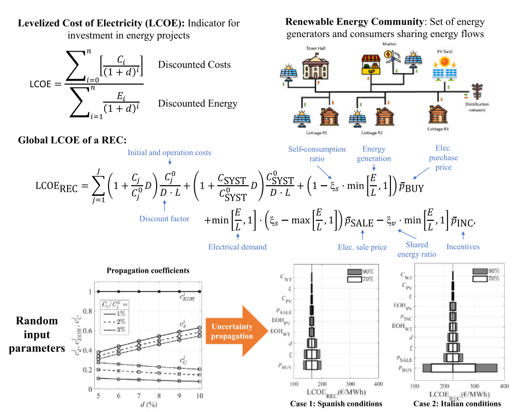
HIGHLIGHTS

- The global LCOE for a typical REC has been defined.
- The uncertainty propagation in the LCOE formulation has been studied.
- The proposed model has been applied to an electrical polygeneration REC.
- As an example, the Spanish and Italian regulatory frameworks have been considered.
- The LCOE of RECs is mainly sensitive to the electricity price and the power load.

GRAPHICAL ABSTRACT



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ABSTRACT

Renewable Energy Communities (RECs) are being deployed all around the World as a technically feasible solution to decreasing users' dependence on fossil fuels. Several demonstration facilities have shown their potential to provide final consumers with clean energy and all associated environmental benefits. However, the economic evaluation of these systems as a whole set is more complex than evaluating generation technologies individually, which can be considered a barrier, and it may be more complicated to calculate its uncertainty with precision. This paper deals with this challenge and adapts a model for the evaluation of the global Levelized Cost of Electricity (LCOE) of a polygeneration microgrid to the characteristics of a typical REC, allowing the assessment of the distribution of the LCOE depending on the uncertainty of the input parameters. Thanks to its simple analytical formulation, the proposed model, that can be used for any combination of technologies (both renewable and conventional), provides relevant information on uncertainty propagation in a symbolic way that avoids the need to run numerical simulations or make assumptions on the distribution of the random input parameters. A case study has been presented, considering a typical small electrical REC with photovoltaic plants and micro wind turbines. Although the model can be defined to any market, as a representative example, it has been evaluated according to the current Spanish and Italian regulations, which are analyzed in depth with

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reference to the scientific literature. Results show that uncertainties in parameter estimates give rise to a very large scatter in the LCOE, pointing out a set of quantities whose role is crucial for a reliable estimate, among which electricity purchase and selling prices, yearly power load, and self-consumption / virtually-shared energy rates stand out.

Nomenclature

Abbreviations

δ_x	Coefficient of variation of x [−]
μ_x	Mean value of x
$\overline{p}_{\mathrm{BUY}}$	Average price of electricity purchased from the external grid [€/MWh]
$\overline{p}_{\mathrm{INC}}$	Average value of incentives for self-consumed or shared energy [€/MWh]
$\overline{p}_{\mathrm{SALE}}$	Average revenue due to the electricity injected in the external grid [€/MWh]
0	As superscript, it refers to the initial value (for year 0) [−]
C	Yearly operation and investment net costs [€/year]
CAPEX	Capital Expenditures [€]
c_x	Propagation coefficient [−]
D	Auxiliary parameter that accounts the total discount
d	Discount rate [%]
E	Generated electricity in a time period [MWh]
E_{GRID}	Yearly electricity purchased from the external grid [MWh/year]
EOH	Equivalent Operating Hours [h/year]
E_{REC}	Yearly electricity absorbed by the REC [MWh/year]
E_s	Yearly self-consumed or shared energy [MWh/year]
E_{SURPLUS}	Yearly surplus electricity injected into the external grid [MWh/year]
f'	Participation factor [−]
I	Time interval [year]
J	Set of generators [units]
K	Set of parameters [−]
L	Yearly electricity demand [MWh/year]
LCOE	Levelized Cost of Electricity [€/MWh]
LCOE′	Levelized Cost of Electricity referred to the lifespan of the installation [€/MWh]
LCOEn	Levelized Cost of Energy [€/MWh]
LROE	Levelized Revenues of Electricity [€/MWh]
n	Useful lifespan [years]
MC	Monte Carlo
OPEX	Operational Expenditures [€/year]
P	Rated power of a generator [MW]
PCC	Point of common coupling
PoD	Point of delivery
PV	Solar photovoltaics
R	Yearly revenues [€/year]
RV	Residual value [€]
TSE	Taylor Series Expansion
WT	Wind turbine
ξ	Simultaneity correction factor [%]
ξ_s	Self-consumed energy ratio [%]
ξ_v	Virtually-shared energy ratio [%]

1. Introduction

The profitability of an investment in the energy sector depends on many factors, namely technical, economic, social, and environmental. Investors must choose the optimal configuration of an energy facility to guarantee the energy needs of end-users by maximizing profits without compromising the environment. Typical economic indicators such as Net Present Value (NPV), Internal Rate of Return (IRR), and Payback Time are employed to evaluate the financial performance of any investment project. However, it is advisable to complement their information with different indicators, such as the Levelized Cost of Energy (LCOEn). Project assessment can use one or more indicators (e.g., [1–3]) or combine them into a comprehensive evaluation [4].

LCOEn is a metric of the unit cost of electricity useful for comparative analyses, or to be compared with the market electricity price [5]. Incorporating the costs incurred during the life cycle of a generation technology, as well as integration and system costs, it can provide a comprehensive metric for evaluating electricity generation projects. Despite a number of limitations [6,7], as oversimplifications of costs and of the project contexts [8], as well as the sensitivity of results to uncertainty in future [9], it is widely used for investments in conventional power generation technologies (steam power plants, combined cycles, and nuclear power stations) and in the renewable energy sector (PV plants, hydro power stations and wind farms). Several national authorities and research bodies publish detailed reports with updated values of LCOEn for different technologies every year. The annual reports published by Lazard [10] and the International Energy Agency (IEA) [11] show several tables and graphs reporting average LCOEn values of conventional and renewable power plants under different operating scenarios (with and without subsides, dependency on fuel prices and carbon taxes, sensitivity to capital and operating costs, etc.). The report by Lazard is focused on the US context, while the report by the IEA includes information from all regions worldwide. In both reports, the historical values of LCOEn are also reported to show how technology improvements in the renewable energy source (RES) sector and capital cost reductions resulted in lower unit energy production costs, thus ensuring the achievement of grid parity for certain RES installed in optimal locations.

Different definitions and variations of the LCOEn can be found in the literature, the most popular being the Levelized Cost of Electricity (LCOE) which refers to the evaluation of the unitary production cost, expressed as currency per unit of energy, of power plants which only produce electricity as a useful effect, such as PV plants, wind turbines, hydro plants, etc. In the case of thermal plants, the Levelized Cost of Heat (LCOH) can be calculated and, when analyzing multi-vector energy systems, where different useful effects (electricity, heating and cooling energy, etc.) coexist, new indicators have to be proposed, such as the Levelized Cost of Exergy (LCOEx), as suggested in our previous work [12].

Most of the studies reported in the literature deal with LCOE of single technologies. On the other hand, Renewable Energy Communities (RECs) are typically fed by multiple generators, i.e. PV plants and wind turbines and a global approach for the LCOE calculation of poly-generation systems is needed. Although the definition of a REC involves multiple energy vectors, in this work, the focus is on electrical systems, such as electrical RECs with PV and wind technologies, which are, to date, the most common ones. Therefore, we will only consider the LCOE, and further analyses concerning multi-vector energy systems will be deepened in future works.

As highlighted in Fig. 1, which has been drawn basing data collected from Scopus database, it is only since 2010 that there has been a sharp increase in the number of scientific articles (published in journal or conference proceedings) reporting in the title and/or the abstract or among the keywords the topics of interest of the present paper, namely "energy communities" and "levelized cost of energy". In 2023, 648 papers reported the term "energy communities" whereas 165 showed the term "renewable energy community"; in the same year, 479 papers reported the term "levelized cost of energy", 369 "levelized cost of electricity" and as many as 673 indicated "LCOE". Italy and Spain are among the five countries from which most of the published papers come, given the strong development of renewables in these countries.

The increase in the number of papers shown in Fig. 1 is mainly due to the massive increase of studies related to the renewable energy sector and to distributed generation. Several investigations report calculation methods of the LCOE of the RES technologies by focusing on different aspects. In [13], a yearly degradation factor for PV production is considered. At the same time, in [14,15], the need to include grid integration costs, namely grid infrastructure costs and balancing costs, is emphasized. Shen et al. [5] describe all the costs and factors that must be considered in the LCOE calculation: investment-related costs, operation-related costs, plant performance information, and risk and uncertainty elements. The authors emphasize the importance of region-specific capacity factors for renewable energy power plants and propose to include cost modeling to account for the impact of intermittent energy sources on the electric power system. Additionally, the authors suggest investigating the correlations among the LCOE parameters and performing Monte Carlo (MC) analyses. In [16], the dependence of LCOE on capacity factor, discount rate, tax rate, and system price is deepened, while in [17], the focus is on how PV module degradation impacts on LCOE. A detailed analysis of the influence of LCOE parameters for different generating technologies is carried out in [18]. In [19], the attention is focused on prosumer households operating in the UK market. A sensitivity analysis is carried out to evaluate the variation of LCOE for PV and medium size wind generators as a function of capital and operating costs, equipment life expectancy, and load profiles. Given the uncertainties in estimating future contexts, LCOE estimates are often accompanied by scenario analyses, considering appropriate variations in key parameters, typically energy prices, and discount rates [9]. In [20], the authors estimate the scattering of LCOE for PV through the Monte Carlo simulation of input quantities, obtained from suitable distributions. Similarly, in [18] a deep analysis is carried out considering a large number of parameters, traditional and renewable plants. The greater uncertainty in estimating RECs' LCOE is widely recognized. Besides Monte Carlo simulations, other methodologies that have been applied to evaluate uncertainty propagation of the input parameters in energy systems can be used as a supplementary aspect for planning renewable energy communities. For investigating the costs of energy technologies, Bosetti et al. [21] recalls different metrics: the sensitivity ratio [22], that quantifies the reduction of the output model variance when the investigated input parameter is fixed, and other indicators that consider the effect related to the change of distribution of the input parameter [23]. In [24] authors review different approaches comprising stochastic programming, based on future scenarios, robust optimization, that use a range of variation for each parameter rather than distributions. These procedures typically necessitate numerical handling, especially when dealing with a multitude of input parameters that defy analytical formulation. Data-driven uncertainty propagation is an emerging research field, whose application in energy systems is primarily directed to design and optimization (e.g., [25,26]).

LCOE is also considered in optimal design models of distributed generation systems and microgrids. For instance, in [27], the authors determine the optimal set of technologies for a stand-alone system with PV, wind turbines, diesel generators, and batteries using multi-objective optimization to minimize costs and life cycle emissions. A similar study is developed in [28], where the evaluation of LCOE is carried out for all optimal solutions of a diesel-PV-battery hybrid microgrid, taking into account various electricity demand scenarios. In [29], a hybrid PV-wind-Stirling engine integrated multi-vector energy system is optimized to minimize LCOE, the loss of power supply, and carbon dioxide emissions, whereas in [30] the authors evaluate LCOE referring to high levels of solar energy penetration into a smart grid system made of several dwellings.

However, only a limited number of the aforementioned works provide a comprehensive evaluation of LCOE considering the coupling of systems, integration costs, and the consideration of the generation technologies as a whole set. When multiple generators are involved, particularly in the case of microgrids and RECs, it becomes crucial to define the reference unit of energy for the total cost calculation (such as energy produced by the set of generators or energy supplied to the distribution network, etc.), without neglecting the costs associated with integrating the different energy sources. As shown in Fig. 2, a small number of scientific papers published between 2000 and 2023 report a combination of the expressions "levelized cost of energy", "levelized cost of electricity", "LCOE", "energy community" and "renewable energy community" in the title and/or the abstract and among the keywords,

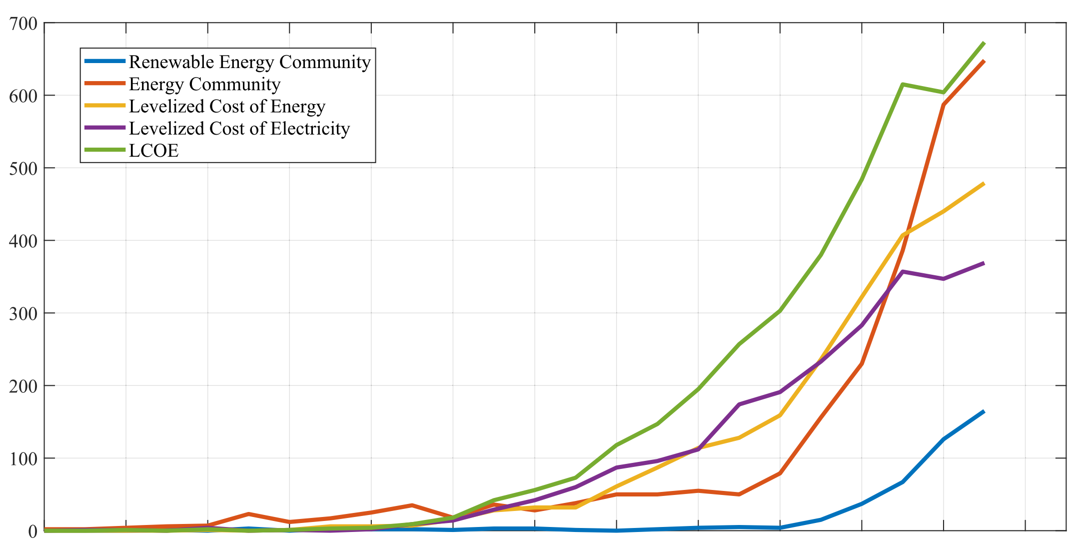


Fig. 1. Number of scientific papers in Scopus from 2000 to 2023 reporting the terms indicated in the legend within title, abstract and keywords.

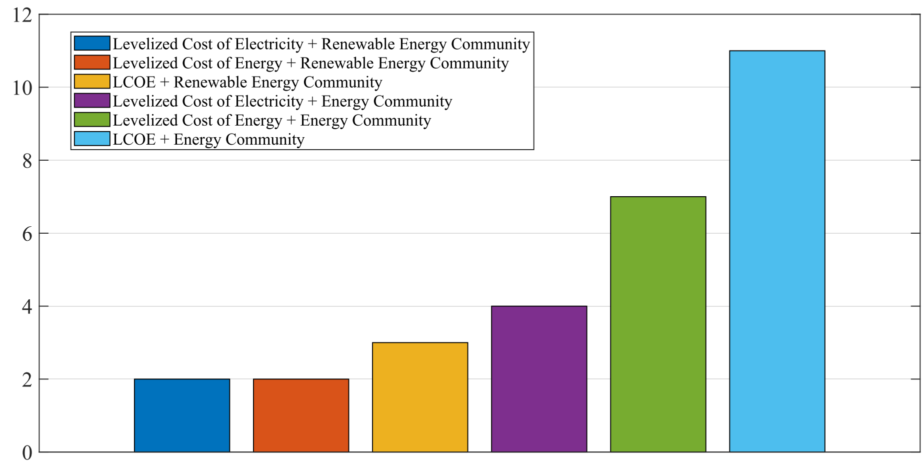


Fig. 2. Number of scientific papers in Scopus from 2000 to 2023 reporting the expressions indicated in the legend within title, abstract and keyword.

this justifying the need to develop LCOE calculation models for energy communities and supporting the present study.

Few papers consider the LCOE of energy communities. In most cases, the authors just analyze specific configurations based on computer simulations, which usually require high-level modeling of each component and a large set of input parameters. In [31], the authors utilize the HOMER Pro software to optimally design and manage different configurations of energy communities made of integrated microgrids. The software calculates the LCOE as a part of the analysis, but no formulations are presented. A similar approach is followed in [32], where the optimal design of a polygeneration system acting as an energy community in a university campus is done with the open-source Calliope framework. The classical formulation used to calculate the LCOE of a single generator is reported in [33], where a methodology to identify the best set of technologies in net-zero energy communities is described. A similar procedure is proposed in [34], which aims to investigate community microgrids, whereas in [35] and in [36] the LCOS (Levelized Cost of Storage) for a community storage system is calculated. Following these considerations, it is worth noting that the literature lacks specific LCOE models for energy communities and the authors found it necessary to develop a comprehensive methodology for this.

This paper introduces three significant novelties covering an existing knowledge gap. Firstly, the authors adapt and simplify a mathematical model they developed for the LCOE calculation of a REC, considering several generators and consumers. Relying on a previous work [12], where a methodology was proposed for calculating the LCOE of polygeneration electrical microgrids, ~~the~~ the proposed approach supplies a simplified formulation for a close and realistic approximation of the global LCOE of an energy community, considering a simple and limited list of parameters easy to calculate or estimate. Secondly, it is applied a probabilistic assessment to analyze the influence of the different input parameters on the global LCOE and evaluate its dispersion. In this way, a direct relationship is provided between the uncertainties in the results and a set of selected parameters. Finally, it is compared the impact of local regulatory frameworks of RECs on the LCOE evaluation. The methodology and the formulas reported in the present paper can be used to study the most common RECs characterized by different generation technologies and subjected to several regulatory frameworks and incentive mechanisms. It is not intended to replace other economic indicators when assessing the feasibility of an investment. Considering that more accurate and comprehensive assessments will be conducted using additional indicators and thorough procedures, its objective is to provide a swift, initial method for conducting preliminary evaluations and comparisons among various solutions. Although the model can be adapted to any regulation and particularized to any combination of technologies, both renewable and conventional, it is primarily designed for a typical electrical REC. The case study described in the paper considers therefore a small REC with solar photovoltaic and wind turbine generators analyzed under both the current Spanish and Italian frameworks.

The remainder of this paper is organized as follows. Section 2 introduces the RECs by illustrating the current legislation in force in Italy and Spain and reporting the main scientific articles dealing with their application and analysis. Section 3 illustrates in detail the methodology proposed to calculate the LCOE of a REC, reports the description of the input parameters and defines the method developed to carry out the analysis of the uncertainty propagation. Then, in Section 4, a numerical application of the proposed model is discussed. First, the authors describe the considered case study, and they present the numerical results by applying the model. The results using both a deterministic approach and a probabilistic assessment are compared. Finally, the main conclusions are drawn in Section 5. Furthermore, to help the reader in better understanding the mathematical aspects of the methodology, two annexes are reported. Annex A summarizes the equations for the LCOE calculation of polygeneration systems without storage, while Annex B provides deeper reasoning of the probabilistic assessment.

2. Renewable energy communities

To better understand the application of the LCOE concept to a REC, it is necessary to define the main characteristics of RECs. A REC, as defined by the EU legislation through Renewable Energy Directive EU 2018/2001 (called RED II Directive) [37], is a legal entity where different members (public or private) share the energy locally produced by RES to satisfy their energy needs [38]. It is characterized by several technical and regulatory aspects, dealing with limited membership (natural persons, SMEs, local authorities including municipalities), primary sources (only RES), proximity constraints (consumers located close to power plants), etc. Each EU member state implements this directive by applying specific rules and restrictions.

In Italy, the provisional implementation of RED II was done by Law 28 February 2020, no. 8. The technical rules to establish a REC derived from specific regulatory acts issued by the Italian Regulatory Authority for Energy, Networks, and Environment (ARERA), with Deliberation 4 August 2020 no. 318/2020/R/EEL, and from technical rules defined by *Gestore Servizi Energetici* (GSE), i.e., the public company promoting renewable sources and energy efficiency. Incentives have been recognized for twenty years to the virtually-shared energy, calculated hourly as the minimum between the electricity produced by RES plants (in operation after March 1, 2020) and injected into the distribution network and the electricity withdrawn by the users from the distribution network. Power plants had to be characterized by a rated power lower than 200 kW, and all the members of the REC had to be connected to the same portion of the low-voltage distribution network derived from the same medium voltage / low voltage substation. A REC is so based on a virtual model where the sharing of the produced electricity is achieved using the existing distribution network. Each member has a dedicated point of delivery (PoD) and can choose its electricity provider [39]. The full implementation of RED II took place with the Legislative Decree no. 199 of 8 November 2021 and the following acts. In particular, the Decree of the Minister of Environment and Energy Security of 7 December 2023, no. 414 (CACER Decree), in force since 24 January 2024, defines the new modalities for the granting of incentives aimed at promoting the installation of plants powered by renewable sources included in configurations of energy communities, groups of self-consumers and remote self-consumers. Moreover, the "Testo Integrato per l'Autoconsumo Diffuso" (TIAD), annexed to ARERA Resolution 727/2022/R/eel, regulates the operating mechanism and the valorisation contributions due to the energy consumed within the authorised configurations. The maximum size of the plant eligible to be included within a REC has been increased to 1 MW and the scope of the community has been extended to include all users connected to the same primary high-voltage/medium-voltage substation.

Similarly, in Spain, the concept of REC was first presented in the *Plan Nacional Integrado de Energía y Clima 2021–2030* (PNIEC) [40], which explicitly promotes mechanisms for the citizen participation in the energy context. Furthermore, Law 24/2013 on the Power Sector [41] defined the concept of self-consumption in Spain. Under this framework, the Royal Decree 244/2019 [42] regulates the administrative, technical, and economic conditions for self-consumption in this country. According to this regulation, it is possible to configure a collective consumption scheme where the users can share the surplus energy generated by the associated generators [43]. In this scenario, any surplus energy injected into the public grid can be financially compensated on a monthly basis [39]. Additionally, valid schemes without surplus can be implemented, where the different members of the REC may exchange energy via a proprietary grid (regulated in Spain through the Royal Decree 314/2023 [44]), while any injection into the national distribution grid is forbidden.

To the date of writing this manuscript, in Spain, a draft of a Royal Decree on the regulation of Renewable Energy Communities and Citizen Energy Communities [45] is under public evaluation and is expected to be approved soon (Law 24/2013 on the Power Sector has just updated to include the definitions of REC and CEC through articles 12bis and 12ter, respectively [41]). The proposed code transposes the European Directives to the Spanish regulation framework, detailing the requisites of RECs and their rights and obligations as legal entities, as well as those of their members. From the technical point of view, according to the current Spanish regulation (which regulates self-consumption facilities), there exists the concept of "collective self-consumption," where a community of prosumers and individual generators can share the produced energy (generators) and the surplus (prosumers) among them and with other "normal" associated electricity consumers. For this modality of collective or shared self-consumption, the partners must fulfill some proximity criteria (e.g., same public or private distribution network). The collective self-consumption can be done with or without surplus. Under the modality without surplus, the collective self-consumers own a system that blocks any injection into the public distribution network. The collectively self-consumed energy is defined as the minimum between the hourly generation and the sum of the individualized hourly self-consumption. When the generation exceeds the overall consumption, the collectively self-consumed energy equals the overall consumption, curtailing excess production. On the other hand, when the prosumers' generation or overall surplus is lower than the total power demand, the self-consumed energy is equal to the overall generation and surplus. Under the modality of collective self-consumption with surplus allowed, the overall surplus of the system can be injected into the public distribution network, and, in some cases, the injected energy can be economically compensated monthly. In both cases, the consumers are billed only by the net consumption from the grid, calculated as the energy consumption in their power meter discounted by the fraction for the user of the shared energy. This fraction can be unique for the whole year or be defined for each hour of the year *ex-ante*.

Being the regulatory framework for RECs quite recent in most countries, the scientific literature on this subject is still evolving. On the other hand, several papers deal with RECs, with some specifically outlining mathematical models used to their optimal sizing and operation. Other ones focus on real RECs, evaluating and critically discussing their economic, environmental, and social benefits. In [46], particular attention is given to the multiple actors involved, highlighting the significance of municipalities in motivating citizens to participate in REC initiatives. As emphasized by [47], the primary expectation from RECs is not necessarily a significant economic gain, but rather the efficient management of energy resources, the increased flexibility, together with environmental and social benefits. A particular aspect also concerns economic income distribution among community members, as reported in [48], where an original and fair method to allocate the economic benefits among the members is discussed. The same authors highlight how the application of demand response strategies and the energy community composition can influence the optimal configuration of the REC.

In [49], a methodology is proposed to assist energy experts and urban planners in the optimal sizing and management of the REC. The study compares different configurations, namely centralized and distributed, where energy can be physically or virtually shared to reduce emissions and energy poverty per the principles defined by the EU regulatory framework. In [50], the authors develop a model for the optimal design of a REC with different technologies and members. They utilize an annual time horizon to better account for the variability of electricity prices and energy quantities during the year.

The application of the REC concept in Italy is investigated in several papers. In particular, in [49], the current implementation of the EU legislation at the Italian level is described. In [51], attention is also pointed to the impact of RECs on the national electric power system, discussing how they could contribute to the widespread adoption of vehicle-to-grid (V2G) and demand response. In [52] RECs are seen as a suitable way to support urban space redevelopment projects in cities, while in [53] the REC model is implemented in Ponza (Italy), a minor island disconnected from the national grid, with strongly seasonal energy load and water demand. This study proves that a REC can achieve economic profitability with a large amount of shared energy when different kind of members (industrial facilities, residential prosumers, residential consumers, restaurants, and hotel prosumers) are present, each one characterized by different load profiles in terms of shape and time of occurrence of peak demands. In [54] a feasibility study to build a REC in the Municipality of Assisi (Italy) is described focusing on the role played by public administrations as catalysts in the formation of RECs. The REC in Villar Pellice (Turin, Italy) is studied in [55], where a methodology to assess its technical-economic feasibility, based on the calculation of self-consumption and the self-sufficiency indexes, is reported. Similar indicators are shown in [56] with the aim to simulate different REC scenarios in different cities and assuming variable capital and operating costs of power generation technologies. One of the first RECs developed in Italy, in Magliano Alpi, is described in [57] through the analysis of annual and monthly operational data collected from smart meters installed on residential customers and small and medium enterprises participating in the community. In [58] the aim of the study is to assess the energy and environmental feasibility of a REC located in Northern Italy using real electricity consumption and thermal energy need data made available from different datasets; different configurations of the REC are optimized considering also the possibility to install small-size cogeneration units coupled with PV systems. The optimal sizing of generation systems for the REC in Riccomassimo, Italy, is proposed in [59] with the aim of optimizing economic, environmental, and social indicators in presence of centralized or distributed PV systems and also taking into account a different number of members. Considerations on the convenience to install centralized or distributed RES systems are also drawn in [60], where the authors propose a roadmap for the constitution of RECs in Italy and show the results of a real application in the residential sector in Catania, Sicily (Italy). A different point of view can be found in [61] where three different options of business model are considered when optimizing a REC, taking also into account the role of an independent company acting as a technological partner to acquire and manage the assets. The study is applied to a real test case of a REC located in the north-western region of Italy, for which several key performance indicators are modeled. In [62] a social housing district in Naples, Southern Italy, acting as a nearly zero-energy community, is described and the importance of optimally operating the charging and discharging of electrical storage systems within RECs is discussed. The optimal operation of a PV system with storage batteries within a prosumer building acting as an energy community is modeled in [63], whereas in [64] the focus is on the application of demand response strategies within RECs. Some considerations on the calculation of the LCOE for a REC based on the exploitation of solar and wind resources are reported in [65], while on [66] a multi-disciplinary approach to design a REC in Vega de Valcarce, a rural community in Spain, is proposed, also basing on the collection of data through a survey. The authors in [67] point the attention to the relations among the different actors operating within a REC. In [68] a techno-economic analysis of the influence of the current regulatory framework on the energy sharing mechanism is deepened, while the study reported in [69] is one of the few ones present in the literature which deal with the adoption of electric mobility infrastructures within a REC. It emerges that some papers on RECs are more focused on social and legal aspects, while others prefer to analyze technical aspects with the aim of optimizing the size and the scheduling of power generation technologies [70–75]. In [76] an optimal energy management system for an energy community is proposed to optimize its operation within the electricity market by the participation to the automatic frequency restoration reserves market in Spain. The paper reports some considerations on LCOE, as also done by the authors in [77], where the impact of different configurations of a REC based on solar and wind turbines combined with a hybrid battery and regenerative hydrogen fuel cell on the LCOE is evaluated. A discussion on different economic indicators, namely LCOE, self-consumption ratio, and self-sufficiency ratio, is reported in [72] where a multi-objective particle swarm optimization to design a REC with RES sources and storage systems is proposed for a rural island. Other interesting considerations on LCOE for energy communities in islands are shown in [71], while [78] the optimal design of a university campus acting as a local energy community is developed with the aim of minimizing the LCOE of the whole energy system. However, there is a lack of detailed LCOE calculation methodology for a REC in the literature and it is therefore believed that the model proposed here may provide interesting points for further development of this important economic indicator.

3. Methods

3.1. The mathematical model for the LCOE calculation

The LCOEn represents the unitary energy production cost over an assumed financial life of *n* years. If only electrical energy is considered, it is possible to define the LCOE, which can be expressed as:

$$\mathrm{LCOE} = \frac{\sum_{i=0}^{n}\left[\frac{C_i}{(1+d)^i}\right]}{\sum_{i=1}^{n}\frac{E_i}{(1+d)^i}}, \tag{1}$$

where *i* indicates the time interval (namely, a specific year); *C* represents the net costs, including capital expenditures (CAPEX) that can occur from the start of the project and during its lifespan (replacement of components, repowering, etc.), operation and maintenance costs (OPEX), fuel, and other input costs, such as externalities. It can also include, as subtractive terms in the formula, possible benefits from internalities or avoided externalities. *E* is the produced electricity, and *d* is the discount rate.

The LCOE can be regarded as the annual average wholesale price at which the energy provided by a generator must be paid to compensate the discounted costs for its whole lifespan, i.e. the discounted revenues compensate the discounted costs. According to this definition, the energy to be considered is the energy that can be effectively injected to the power grid, as the curtailed energy will not be purchased.

The extension of the definition of the LCOE, which may seem simple for a single generator, is not as immediate for complex systems such as RECs. If we model a REC as a microgrid, we must consider several generators and power loads. Some authors, e.g., [79], consider the total energy consumption, rather than the produced energy and include the grid supply as an additional cost. Other authors, on the contrary, derive the LCOE from the total aggregated costs of all the generators and the total energy generated [80]. In this work, we propose to consider the REC as a solid entity which energy balance can be expressed as:

$$E + E_{\mathrm{GRID}} = E_{\mathrm{REC}} + E_{\mathrm{SURPLUS}}, \tag{2}$$

where *E* is the sum of the energy supply from all the generators in the REC, E_{GRID} is the energy purchased from the external grid when the energy provided by the internal generators is not sufficient, E_{REC} is the energy provided to the power loads to the REC, including power losses, and E_{SURPLUS} is the energy injected back to the public power grid as the internal generation capacity exceeds the power demand of the REC.

Paralleling the approach used for a single generator, the LCOE for a REC, hereinafter referred to as $\mathrm{LCOE}_{\mathrm{REC}}$, is evaluated by considering the usable energy, i.e., the energy supplied to the REC. Generalizing Eq. (1) to a REC modeled as a poly-generation electrical system without storage (for the sake of simplicity) and with *J* power plants connected to the electrical distribution network, $\mathrm{LCOE}_{\mathrm{REC}}$ is obtained by generalizing the LCOE provided in [12] for an electrical microgrid:

$$\begin{aligned}\mathrm{LCOE}_{\mathrm{REC}} = \sum_{j=1}^{J}\left(f''_j \cdot \mathrm{LCOE}'_j\right) + \mathrm{LCOE}''_{\mathrm{SYST}} + f''^{\mathrm{GRID}}_{\mathrm{BUY}} \cdot \mathrm{LCOE}_{\mathrm{GRID}} \\ - f''^{\mathrm{GRID}}_{\mathrm{SALE}} \cdot \mathrm{LROE}_{\mathrm{GRID}},\end{aligned} \tag{3}$$

where LCOE'_j is the LCOE of the *j*-th electrical generator referred to the lifespan of *n* years of the whole installation (not all the generators or components in the REC may have the same lifespan), $\mathrm{LCOE}''_{\mathrm{SYST}}$ indicates the virtual LCOE for the system costs (integration and coordination of generators and loads, internal infrastructure, and others), $\mathrm{LCOE}_{\mathrm{GRID}}$ is the Levelized Cost of Electricity purchased from the distribution grid, while $\mathrm{LROE}_{\mathrm{GRID}}$ is the Levelized Revenue due to the surplus electricity injected into the distribution grid. Terms f'' indicate the participation or ponderation factors of each component referred to the energy served to the REC. Extended expressions for the described terms are reported in Annex A, summarized and adapted from [12]. This way, the participation factors allow to calculate the aggregated LCOE for the REC as a function of the individual LCOE of each generator, system or the electricity of the external grid, which may be useful.

Eq. (3) requires information on quantities averaged over each year throughout the expected lifespan of the installation. In techno-economic applications, suitable nominal constant values are frequently assumed, allowing for a significant simplification. It must be highlighted that the proposed formulation is also applicable to model off-grid systems by considering that no energy is interchanged with the external grid and adequately adjusting the production of the generators (and consequently, their real associated LCOE values due to this operation mode). For simplicity, the presented model version does not consider the integration of a battery energy storage system, which will be derived in future investigations.

Revisiting the formulation presented in Annex A, it is assumed that yearly quantities at year $i = 1...n$ are constant and that installation costs are incurred at year 0. Superscript i is omitted in the following. Posing these assumptions in Eq. (4), $C_j^i = C_j$ represent the yearly net costs, for $i = 1...n$, C_j^0 is the net cost of the installation; $E_j^i = E_j$ represent the energy produced yearly by the j-th generator. It can be calculated as the product of its rated power P_j and its yearly equivalent operating hours EOH_j, i.e., $E_j = EOH_j \times P_j$. The following formula for the LCOE of the j-th generation unit derives:

$$\text{LCOE}_j = \frac{1}{E_j}\left(\frac{C_j^0}{D} + C_j\right), \tag{4}$$

being $D = \sum_{i=1}^{n} \frac{1}{(1+d)^i}$. Eq. (4) includes replacement costs of generators or system parts (e.g., inverters of PV power plants) either pro-rated along the generator's lifespan (and included in the OPEX) or with their present value added to the CAPEX.

Renewable Energy Communities, made of different users connected to the distribution network, absorb or inject electricity from/into the public network through a certain number of points of common coupling, each one referring to a single user or a power plant. The hourly self-consumption, as defined by the Spanish regulatory framework, or the hourly virtually-shared energy (energy consumed by all users as it was directly supplied by the generators), in accordance with the Italian regulation, is set as the smallest value between the total injected electricity and the total load. With the aim of framing the discussion in terms of annual average values, in a simplified way the self-consumption or virtually-shared energy can be calculated over a complete year as the self-consumed (or virtually-shared) energy E_s expressed as a fraction of the smallest value between the total yearly generated electricity E and the total yearly load L:

$$E_s = \xi \cdot min(E, L), \tag{5}$$

where $E = \sum_{j=1}^{J} E_j = \sum_{j=1}^{J} P_j \cdot \text{EOH}_j$, and ξ is a simultaneity correction factor in the range $[0, 1]$ to model the hourly simultaneity of generations and loads. In this model, E_s is approximated on a yearly-basis but, the self-consumed or virtually-shared energy can be calculated hour by hour when real measured data are available. The adopted approach allows the calculation of the global LCOE without accurate information on the power load profiles and hourly generation profiles of RES generators. Although Eq. (5) appears to be a simplification compared to making an hourly calculation, it is useful in all those cases where one wants to estimate the LCOE even though user hourly load profiles are not available, but only monthly or annual energy consumptions are known. This is a very common case as, for example, in Italy where only a small portion of low-voltage consumers already have the latest generation of smart meters installed. The exact determination of reference values for the proposed self-consumption (or virtually-shared) energy fraction according to the characteristics of the generators and consumers is out of the scope of this work, but according to some numerical simulations, values between 0.6 and 0.8 can be suitable.

Finally, in some cases, the REC can take advantage of economic incentives proportional to the shared energy. Such incentives can be considered as positive internalities that can be estimated as the product of the self-consumed or virtually-shared energy, and the annual average value of the incentives $\overline{p}_{INC}$.

Considering the above-described assumptions and simplifications, and assuming moreover that the lifespan of each units aligns with the lifespan of the overall installation, the revisiting of the formulation presented in Annex A according to the provided assumptions allows rewriting Eq. (3) using the following straightforward expression:

$$\begin{aligned}\text{LCOE}_{\text{REC}} = {} & \sum_{j=1}^{J}\left(1+\frac{C_j}{C_j^0}D\right)\frac{C_j^0}{D \cdot L} + \left(1+\frac{C_{\text{SYST}}}{C_{\text{SYST}}^0}D\right)\frac{C_{\text{SYST}}^0}{D \cdot L} \\ & + \left(1-\xi_s \cdot min\left[\frac{E}{L},\,1\right]\right)\overline{p}_{\text{BUY}} \\ & + min\left[\frac{E}{L},\,1\right]\cdot\left(\xi_s - max\left[\frac{E}{L},\,1\right]\right)\overline{p}_{\text{SALE}} - \xi_v \cdot min\left[\frac{E}{L},\,1\right]\overline{p}_{\text{INC}},\end{aligned} \tag{6}$$

where $\xi_s = \xi$ and $\xi_v = 0$ in case of self-consumption (Spanish case), while $\xi_s = 0$ and $\xi_v = \xi$ in case of virtually-shared energy (Italian case); C_{SYST} and C_{SYST}^0 are the integration and coordination costs for integrating the units and handling the grid in the different years and the installation year, respectively; $\overline{p}_{\text{BUY}}$ and $\overline{p}_{\text{SALE}}$ indicate the average unit price of the energy purchased and sold from/to the main grid.

Eq. (6) is expressed in terms of C_j / C_j^0 and $C_{\text{SYST}} / C_{\text{SYST}}^0$ on purpose as yearly costs are usually indicated as proportional to the CAPEX.

In the case of off-grid communities (e.g., [81,82]), the presented model can be also applied adopting the appropriate considerations, i.e., assuming that no energy is exchanged with the external grid and adequately adjusting the production of the generators (and consequently, their real associated LCOE values due to this operation mode). For simplicity, as already said, the presented model version does not consider the integration of storage batteries, which will be added to the model in future investigations.

3.2. Model parameters

Eq. (6) depends on the eight types of input parameters:

i. Capital Expenditures (C_j^0, C_{SYST}^0): they represent the capital costs for the single generator and total costs inside the plant boundaries, including the civil engineering or any wiring, piping, or other auxiliaries installed within the plant. They are short-term costs that can be reliably established.

ii. Operational Expenditures (C_j, C_{SYST}): they represent a yearly estimate of the total operating costs and revenues over the project design life, related to the specific power units and the whole system, respectively. They include operation, energy supplies, and maintenance. Maintenance interventions on small-size renewable energy systems and their accurate prediction can significantly affect the profitability of the installation. PV solar systems have a relatively simple design with no moving parts. Therefore, they are less exposed to damages and unexpected events. In contrast, small wind turbines have complex mechanical systems requiring frequent maintenance and repair, thus making maintenance costs uncertain [83].

    Operational expenditures also include internalities, given by indirect benefits for the stakeholders not directly related to the amount of produced energy, and externalities, provided by the costs or benefits to society from the power plants not presently considered by the market price [84,85]. Translating externalities into monetary terms poses obvious difficulties [86], so they are often excluded from cost-benefit estimates. Given the increasing focus on pollutant emissions, there are directions at the European level to translate these kinds of externalities in economic terms (e.g., [87,88]). Also in this case, however, large uncertainties exist, impacting a long-term global externality.

iii. Discount rate (d): it calculates the present value of money that will be received or paid in the future. From a private perspective, the discount rate should represent the opportunity cost of what the company could obtain with those funds. From a social policy point of view (thus looking at the benefits for the community), the choice of a social discount rate reflects the social perspective on how the future should be valued against the present. In this case, average values should not exceed 4–5% for the European countries [89] and be even smaller [90]. Small changes in this rate can result in large fluctuations in present-value calculations of energy costs. Sensitivity analyses are usually carried out considering different values around a base scenario (e.g., 1%–5%, [91]; 3%–15%, [89]).

iv. Electric load *(L)*: it represents the electricity consumption that varies in time during the day and the season according to the user type. The prediction of this quantity has important limitations and is inherently uncertain (e.g., [92–94]).

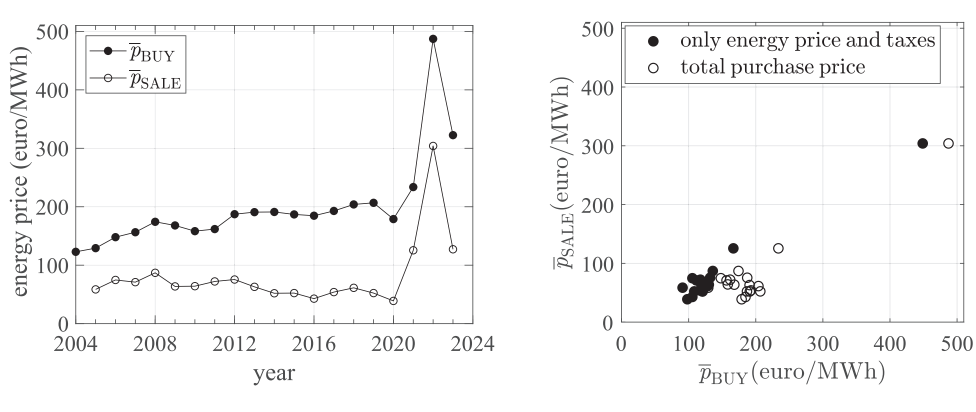
v. Electricity prices for electricity purchase and sale ($\overline{p}_{\mathrm{BUY}}, \overline{p}_{\mathrm{SALE}}$): they depend on variegated factors, such as supply and demand, generation mix, transmission and distribution costs, regulatory environment, time of use and seasonal variations, and geopolitical events. Especially in recent years, the variability of electricity prices has been significant due to multiple factors, including the impact of the COVID-19 pandemic and changing international scenarios. Fig. 3(a) reports the average annual prices for electricity in Italy. $\overline{p}_{\mathrm{SALE}}$ is assumed according to the PUN (Single National Price), which is the wholesale reference price of electricity that is purchased on the IPEX - Italian Power Exchange [95]. $\overline{p}_{\mathrm{BUY}}$ is assumed according to price of electricity for the standard domestic consumer [96]; it is the sum of different components, related to the price of energy, transportation and meter management, system charges, and taxes. Huge price variations are particularly evident from 2020 onward, such that this quantity is extremely volatile. Fig. 3(b) reports electricity sale price versus purchase price (white circles), showing a sound correlation between these two quantities (correlation coefficient 0.92), considering only the component due to the cost of energy and taxes in $\overline{p}_{\mathrm{BUY}}$ (full black dots), the correlation between the two values becomes a close unit (correlation coefficient 0.98).

vi. Incentives ($\overline{p}_{\mathrm{INC}}$): different kinds of incentives can be introduced to remunerate the self-consumed or virtually-shared energy. These incentives can compensate the system costs incurred to annually manage the REC (generation and consumption monitoring, maintenance of smart meters and other ICT devices, etc.). The adoption of specific incentives depends on the policies implemented by governments when adhering to EU regulations. In Italy, where the "Jointly acting renewable self-consumers" and "Renewable Energy Communities" schemes are recognized by law, specific incentives (expressed as €/MWh) are applied to the virtually-shared energy calculated on an hourly basis [39]. Moreover, variable components of transmission and distribution grid charges are also returned. In Spain, where different schemes of renewable collective self-consumers have been implemented, no specific incentives are adopted by the moment. Still, compensation between the surplus energy injected into the distribution network and the one bought is applied [12].

vii. Equivalent operating hours (EOH_j): this indicator synthesizes several factors related to the energy production for each generation unit. It is a random quantity affected by the intermittency of the source (e.g., solar radiation, wind speed, hydro potential, sea waves), the uncertain behavior of the in-field installation, energy demand, etc. Among the power units considered in the following sections, small wind turbines are the technology with the greatest uncertainties in the energy production forecast [97]. [98] reports a general survey of WTs in Italy classified according to the installed power. By way of example, for target power 20–60 kW, the average EOH estimated on a sample of 744 units is 1352 h/year and the standard deviation is 926 h/year. Besides the low average production level, data highlight considerable heterogeneity, which is further increasing for smaller plants, much exposed to wind gusts and turbulence [99]. Other surveys (i.e., [100]) show similar results, as factors such as maintenance, wind-induced damage, and poor quality of components contribute to this inconsistency [101]. On the other hand, the prediction of average EOH for PV systems is easier when the plant location and installation angles (azimuth and tilt) are known; different software tools, such as PVGIS [102], and several reports available online, provide datasets for EOH evaluation [103].

viii. Self-consumption rate (ξ_s) / virtually-shared energy fraction (ξ_v): as previously seen, the self-consumed or virtually-shared energy is calculated yearly. For instance, in Italy, the shared energy, which can benefit from incentives, has to be calculated hourly as the minimum between the electricity injected by RES plants into the distribution network and the electricity withdrawn by the users from the distribution network. Since, in contrast, the proposed mathematical model is based on an annual calculation, the self-consumed (or virtually-shared) energy E_s defined by Eq. (5) must be calculated yearly. This simplification determines the necessity to make some assumptions about the simultaneity of electricity generation and consumption; for this purpose, the factors ξ_v and ξ_s ranging from 0 and 1 are introduced in the model.

Given the challenge of statistically characterizing these quantities, studies addressing uncertainty propagation in energy systems employ different distribution models. In [18,104], normal, lognormal, uniform, and exponential distributions are adopted to discuss the LCOE of different traditional and renewable energy technologies. In [20] costs for solar technology follow normal distributions, while discount rate is described by a triangular one, as in [104]. Ioannou et al. [105] use normal distribution for assessing the costs of an off shore wind farm and



(a) *(b)*

Fig. 3. Electricity prices in the Italian market. (a) Electricity prices for purchase and sale. (b) Sale price versus purchase price.

the discount rate. These variegated choices do not seem to be based on specific statistical analyses but are assigned based on reasonably acceptable assumptions.

3.3. Uncertainty propagation

The proposed model for LCOE defined in Eq. (6) has a set of P input parameters $\boldsymbol{X} = [x_1, x_2, .., x_P]$ related to the generators' capacities, the grid energy purchase prices, the system integration, the self-consumption or virtually-shared energy rates, and revenues from incentives. The estimate of all these quantities is uncertain, and errors in the estimates propagate over the LCOE evaluation, either softened or intensified, revealing that conventional assessments, based on nominal values, can lead to overestimates or underestimates, compromising the validity of the results. Therefore, for a comprehensive evaluation of the LCOE, it is essential to have knowledge of the parameter distributions and employ a suitable procedure for propagating uncertainties. Unfortunately, statistical information is often scarce, making it challenging to establish the mean value and standard deviation of the parameters. Indeed, a robust analysis about the LCOE scenarios can be relevant to investors.

By applying the Taylor Series Expansion to the functional relationship LCOE $= f(X)$, and applying the statistical operators, we can obtain the statistical moments of the target quantity according to the information available on the statistical moments of the input parameters. Expanding up to the first order and applying the mean and variance operator, the mean value μ_{LCOE} and the coefficient of variation δ_{LCOE} derive (see Annex B for more details):

$$\mu_{\mathrm{LCOE}} \simeq \mathrm{LCOE}\left(\mu_{x_1}, \mu_{x_2}, \ldots, \mu_{xp}\right), \tag{7}$$

$$\delta^2_{LCOE} \simeq \sum_{p,q=1}^{P,Q} \delta^2_{LCOE,x_p,x_q}, \tag{8}$$

where $\delta_{\mathrm{LCOE}} = \sigma_{\mathrm{LCOE}}/\mu_{\mathrm{LCOE}}$ whereas σ_{LCOE} is the standard deviation of LCOE.

Eq. (7) provides the mean value of the LCOE using Eq. (6) as a function of the mean value of each uncertain input parameter. Eq. (8) provides its coefficient of variation as the sum of contributions related to each pair x_p, x_q and their correlation. Each contribution is given by the product of two terms, respectively quantifying the sensitivity to the parameters and their variability:

$$\delta^2_{LCOE,x_p,x_q} = \left(c^{LCOE}_{x_p} \cdot c^{LCOE}_{x_q}\right)\left(\rho_{x_p,x_q} \delta_{x_p} \delta_{x_q}\right), \tag{9}$$

$c^{LCOE}_{x_k}$ $(k = p, q)$ is the propagation coefficient that relates the variation of LCOE to the variation of x_k:

$$c^{LCOE}_{x_k} = \frac{\mu_{x_k}}{\mu_{\mathrm{LCOE}}} \frac{\partial \mathrm{LCOE}}{\partial x_k}\bigg|_{\mu_{x_1},\ldots,\mu_{x_k},\ldots,\mu_{x_P}} (k = p, q), \tag{10}$$

ρ_{x_p,x_q} is the correlation coefficient of x_p, x_q; $\delta_{x_k} = \sigma_{x_k}/\mu_{x_k}$ is the coefficient of variation of x_k, σ_{x_k} and μ_{x_k} are, respectively, its standard deviation and mean value.

When dealing with statistically independent parameters ($\rho_{x_p,x_q} = 1$, for $p = q$; $\rho_{x_p,x_q} = 0$ for $p \neq q$), Eq. (8) simplifies the calculation further:

$$\delta^2_{LCOE} \simeq \sum_{p=1}^{P} \delta^2_{LCOE,x_p}, \tag{11}$$

where:

$$\delta_{LCOE,x_p} = \left|c^{LCOE}_{x_p}\right| \cdot \delta_{x_p} \tag{12}$$

is the contribution of each parameter x_p.

Different scenarios can arise. When $c_{x_p} > 1$, uncertainties in x_p are amplified. Therefore, even minor errors in the parameter propagate over the LCOE, giving rise to a large scatter. In this case, x_p should be evaluated accurately for a proper LCOE estimation. On the other hand, when $c_{x_p} < 1$, uncertainties in x_p are softened. However, they can cause large scatter in the results when uncertainties on x_p are considerable (i.e., δ_{x_p} large).

If we apply the expression for the calculation of the LCOE of a single generator defined in Eq. (4), then Eq. (10) supplies the propagation coefficients for the input variables. These are the discount rate, the equivalent operating hours, and the operational costs in proportion to the initial costs C_j/C_j^0. It derives:

$$c^j_d = \frac{d}{D} \frac{D'}{1 + \frac{C_j}{C_j^0} D}, \tag{13}$$

$$c^j_{EOH} = -1, \tag{14}$$

$$c^j_C = \frac{D \frac{C_j}{C_j^0}}{1 + \frac{C_j}{C_j^0} D}, \tag{15}$$

being $D' = \sum_{i=1}^{n} \frac{i}{(1+d)^{i+1}}$. We can observe that the propagation coefficients of the generator only depend on d and the ratio C_j/C_j^0. Fig. 4 shows the propagation coefficients versus the discount rate d for a suitable fixed value for C_j/C_j^0 of 1%, 2%, and 3%, highlighting the main role of parameter EOH.

The application of Eq. (10) to Eq. (6) supplies the propagation coefficients of the parameters for the LCOE assessment of the REC. Following the discussion in Section 3.2, the investigated parameters are the equivalent operating hours and the operating costs for each generator j, the discount rate, the unit price for the electricity purchased and sold from/to the external grid, the load, the ratio of either self-consumed or virtually-shared energy on an annual base and the incentives. Capital Expenditures are assumed according to deterministic nominal values.

The following expressions of the propagation coefficients are derived, considering that ξ_v and $\overline{p}_{\mathrm{INC}}$ are equal to 0 when the REC only benefits from self-consumption (e.g., under the Spanish regulation), while $\xi_s = 0$ when the REC benefits from the incentives for supplying energy to the power grid (as for the Italian regulation). For the sake of simplicity, all terms in the following equations represent mean values (e.g., $\mathrm{LCOE_{REC}} = \mu_{\mathrm{LCOE_{REC}}}$, $x_p = \mu_{x_p}$).

- Discount rate:

$$c^{LCOE}_d = -\frac{\sum_{j=1}^{J} C_j^0 + C^0_{\mathrm{SYST}}}{L} \frac{D'}{D^2} \frac{d}{\mathrm{LCOE_{REC}}}. \tag{16}$$

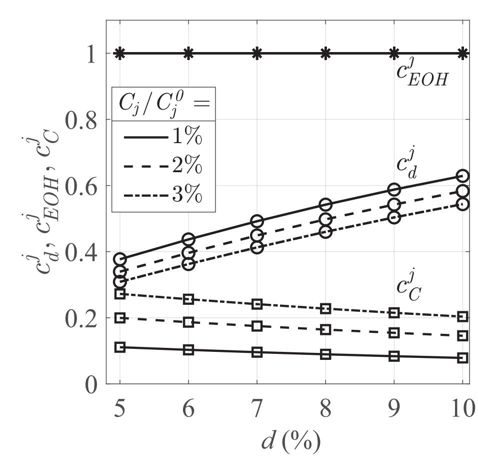


Fig. 4. Propagation coefficients of the input parameters of the LCOE for a single generator.

- Operating costs of generator j:

$$c_{C_j}^{LCOE} = \frac{C_j}{L}\frac{1}{\mathrm{LCOE_{REC}}}. \tag{17}$$

- Equivalent operating hours of generator j:

$$c_{EOH_j}^{LCOE} = -\frac{P_j \cdot \mathrm{EOH}_j}{L}\frac{\overline{p}_{\mathrm{SALE}}}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{18}$$

$$c_{EOH_j}^{LCOE} = -\frac{[\xi_s \cdot \overline{p}_{\mathrm{BUY}} + (1-\xi_s)\overline{p}_{\mathrm{SALE}} + \xi_v \cdot \overline{p}_{\mathrm{INC}}]}{L}\frac{\mathrm{EOH}_j \cdot P_j}{\mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{19}$$

- Load:

$$c_L^{LCOE} = \frac{-1}{L}\left[\sum\nolimits_{j=1}^{J}\left(\frac{C_j^0}{D}+C_j\right)+\frac{C_{\mathrm{SYST}}^0}{D}+C_{\mathrm{SYST}}-E \cdot \overline{p}_{\mathrm{SALE}}\right]\frac{1}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{20}$$

$$c_L^{LCOE} = \frac{-1}{L}\left[\sum\nolimits_{j=1}^{j}\left(\frac{C_j^0}{D}+C_j\right)+\frac{C_{\mathrm{SYST}}^0}{D}+C_{\mathrm{SYST}}-\xi_s \cdot E \cdot \overline{p}_{\mathrm{BUY}}-(1-\xi_s)E \cdot \overline{p}_{\mathrm{SALE}}-\overline{p}_{\mathrm{INC}} \cdot \xi_v \cdot E\right]\frac{1}{\mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{21}$$

- Self-consumed energy ratio:

$$c_{\xi_s}^{LCOE} = \xi_s \frac{\overline{p}_{\mathrm{SALE}} - \overline{p}_{\mathrm{BUY}}}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{22}$$

$$c_{\xi_s}^{LCOE} = \frac{\xi_s \cdot E}{L}\frac{\overline{p}_{\mathrm{SALE}} - \overline{p}_{\mathrm{BUY}}}{\mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{23}$$

- Virtually-shared energy ratio:

$$c_{\xi_v}^{LCOE} = \frac{-\overline{p}_{\mathrm{INC}} \cdot \xi_v}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{24}$$

$$c_{\xi_v}^{LCOE} = \frac{-E \cdot \overline{p}_{\mathrm{INC}} \cdot \xi_v}{L \cdot \mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{25}$$

- Electricity purchase price:

$$c_{\overline{p}_{\mathrm{BUY}}}^{LCOE} = (1-\xi_s)\frac{\overline{p}_{\mathrm{BUY}}}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{26}$$

$$c_{\overline{p}_{\mathrm{BUY}}}^{LCOE} = \left(1-\frac{\xi_s \cdot E}{L}\right)\frac{\overline{p}_{\mathrm{BUY}}}{\mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{27}$$

- Electricity selling price:

$$c_{\overline{p}_{SALE}}^{LCOE} = \left(\xi_s - \frac{E}{L}\right)\frac{\overline{p}_{\mathrm{SALE}}}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{28}$$

$$c_{\overline{p}_{SALE}}^{LCOE} = (\xi_s - 1)\frac{E}{L}\frac{\overline{p}_{\mathrm{SALE}}}{\mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{29}$$

- Incentives:

$$c_{\overline{p}_{INC}}^{LCOE} = \frac{-\overline{p}_{\mathrm{INC}} \cdot \xi_v}{\mathrm{LCOE_{REC}}}, \text{for } L < E. \tag{30}$$

$$c_{\overline{p}_{INC}}^{LCOE} = \frac{-\xi_v \cdot E \cdot \overline{p}_{\mathrm{INC}}}{L \cdot \mathrm{LCOE_{REC}}}, \text{for } L \geq E. \tag{31}$$

4. Numerical application

4.1. Description of the case study

This section illustrates and discusses the application of the proposed formulation to a REC with PV plants and small-size WTs, taking inspiration (data are estimated) from a typical configuration of a REC in a small village. The loads of the REC are represented by a Town Hall, three cottages, and a marketplace. The Town Hall has a PV plant, wo cottages are also equipped with PV, while the market has a hybrid installation of a PV generator and a wind turbine. Finally, the system includes an independent PV generator not associated with any particular consumer.

Fig. 5 illustrates the system scheme, providing a visual representation of the REC. The applied approach simplifies the set up by considering generation plants with a dedicated point of common coupling to the distribution network. This assumption facilitates the calculation of E_s in Eq. (5).

Table 1 reports the electricity demand of each consumer and provides details about the installed generators (size, equivalent operating hours, installation, and operational costs).

An hourly system simulation has been carried out considering typical load profiles provided by HOMER Energy Software [106]. In contrast, the PV generation profiles have been modeled using PVGIS [102]. The wind generation profile has been obtained using the wind speed data recorded by a sonic anemometer in the Savona Harbour (as part of the European Project "Wind and Ports" [107]) and the power curve of the 20 kW vertical axis wind turbine installed in the harbour facility [108]. For reference of the system's behavior, Fig. 6 shows the annual energy flows monthly, while Fig. 7(a) shows a typical winter day and Fig. 7(b) a typical summer day.

Two different cases are analyzed, representative of Spanish and Italian realizations, respectively:

- Case 1 (Spanish configuration): the REC benefits from self-consumption without any incentives. In line with a scenario survey for the last years, average electricity prices are assumed, namely $\overline{p}_{\mathrm{BUY}} = 150$ €/MWh and $\overline{p}_{\mathrm{SALE}} = 50$ €/MWh.
- Case 2 (Italian configuration): the energy surplus produced in the REC is injected into the external distribution grid and sold at $\overline{p}_{\mathrm{SALE}}$, while the collective virtually-shared energy, calculated following current legislation [12], benefits from the economic incentive $\overline{p}_{\mathrm{INC}}$. Then, the electricity coming from the external grid is paid at $\overline{p}_{\mathrm{BUY}}$. In line with a scenario survey, the following input data are assumed: $\overline{p}_{\mathrm{BUY}} = 250$ €/MWh, $\overline{p}_{\mathrm{SALE}} = 80$ €/MWh and $\overline{p}_{\mathrm{INC}} = 119$ €/MWh.

In both cases, the initial costs considered for installing and integrating all the devices of the REC are $C_{\mathrm{SYST}}^0 =$ € 5000; yearly costs for operating the REC are represented by $C_{\mathrm{SYST}} = 600$ €/year; self-consumption / virtually-shared energy rate is assumed as $\xi = 0.7$ (in accordance with the hourly simulation); discount rate $d = 5\%$.

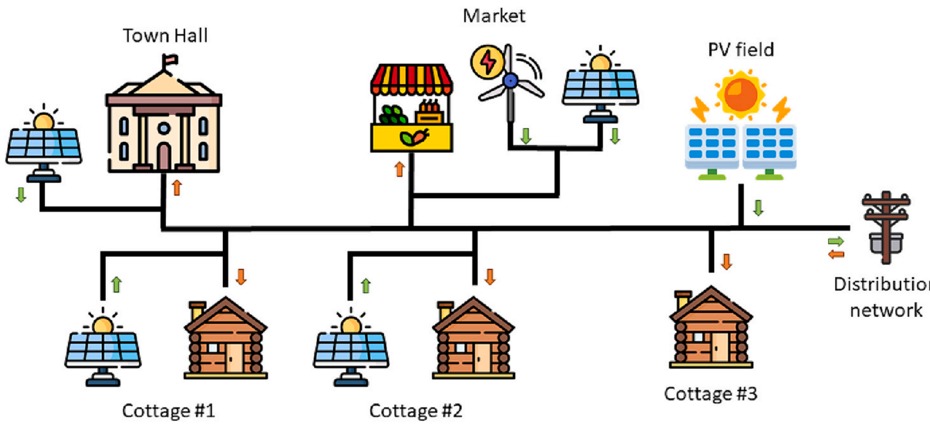


Fig. 5. General scheme of the simulated REC*.
*Picture designed using pictograms from Flaticon.com.

Table 1
Main data of the REC.

User / Gen.	Load	Installed solar photovoltaic (PV)				Installed wind turbine (WT)			
	Energy [MWh/yr]	*P* [kW]	EOH [h/yr]	C^0 [€/kW]	*C* [€/kW/yr]	*P* [kW]	EOH [h/yr]	C^0 [€/kW]	*C* [€/kW/yr]
Town Hall	110	40	1250	1570	16	0	–	–	–
Market	152	50	1250	1570	16	20	1314	4000	25
Cottage #1	3.2	6	1250	1570	16	0	–	–	–
Cottage #2	3.8	10	1250	1570	16	0	–	–	–
Cottage #3	2.4	0	–	–	–	0	–	–	–
PV field	–	50	1250	1570	16	0	–	–	–

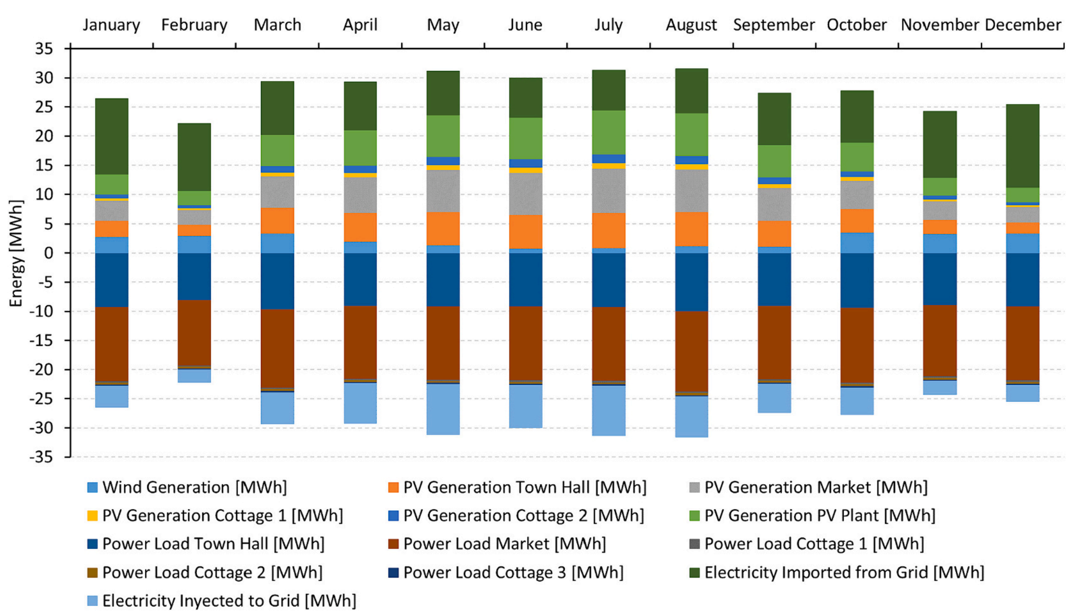


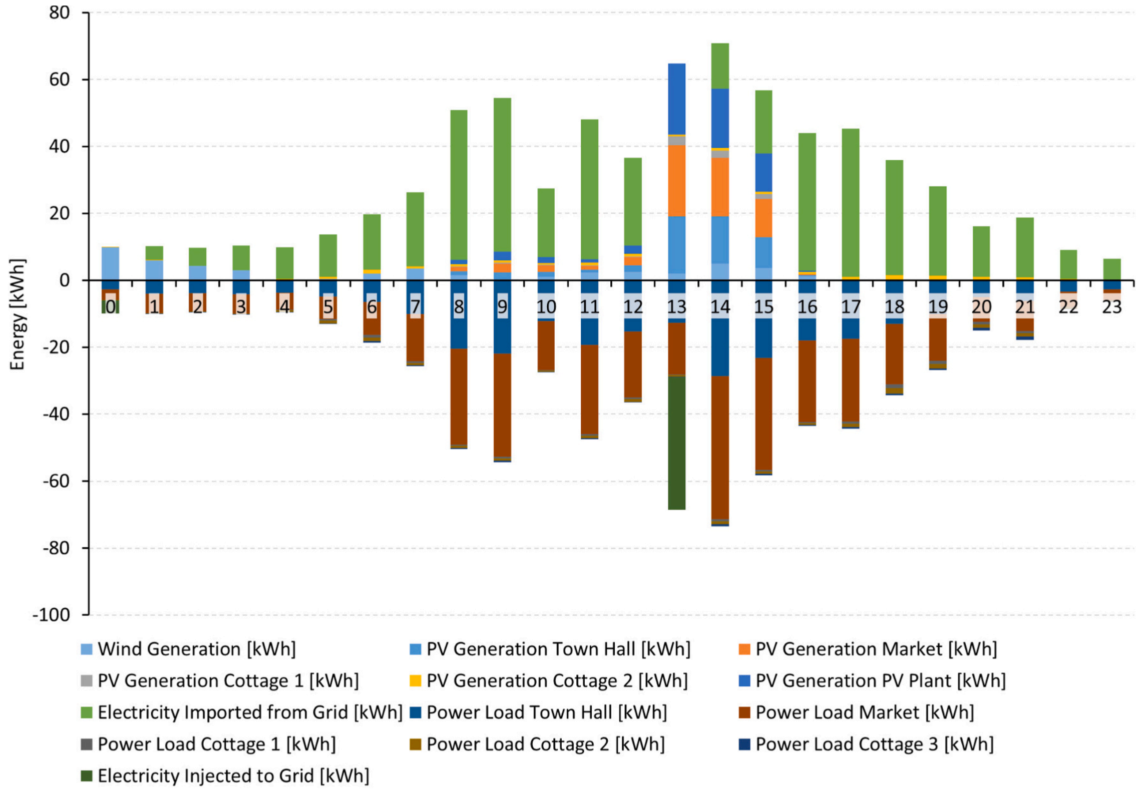
Fig. 6. Aggregated annual energy flows in the simulated REC.

Avoided GHG emissions should be furtherly quantified into economic value [87]. However, since this contribution is somehow already included in the concessions to RECs according to current regulations, we did not consider it in our study.

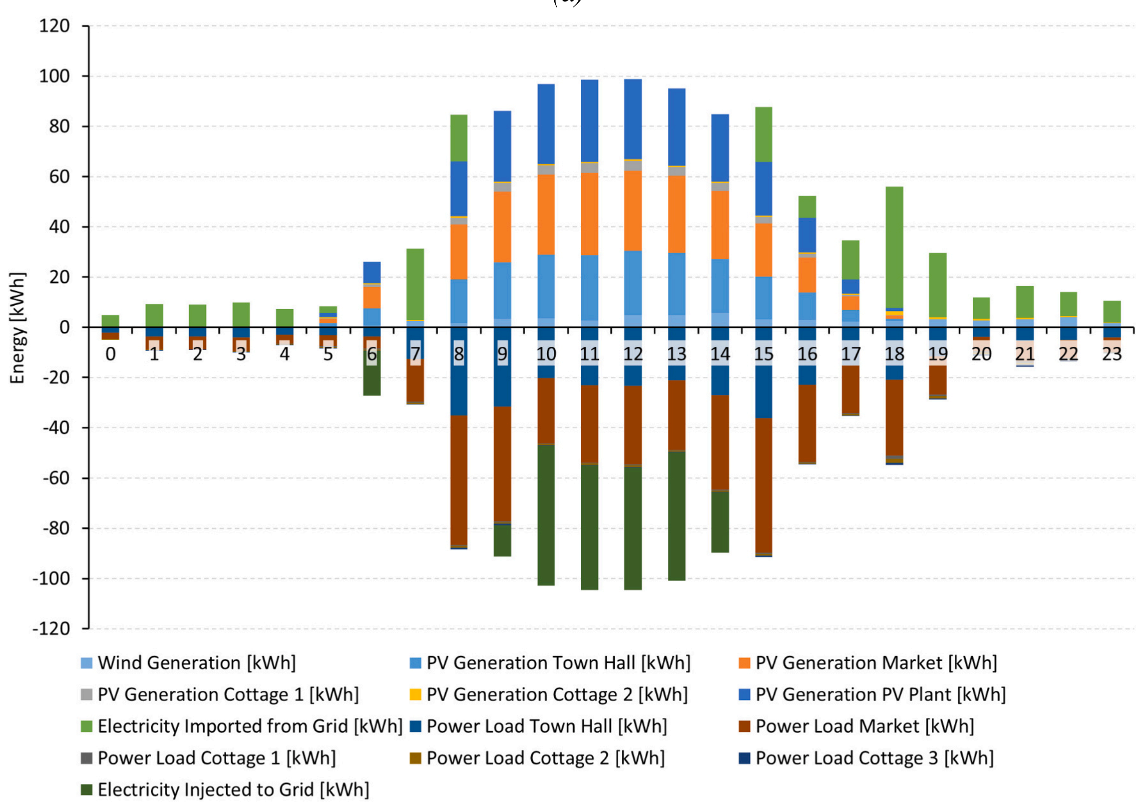
4.2. Results

First, the LCOE is calculated from a deterministic approach. The total amount of the yearly produced energy is $E = 221$ MWh, while the LCOE of the PV generators and the WT are $\mathrm{LCOE_{PV}} = 114$ €/MWh and $\mathrm{LCOE_{WT}} = 263$ €/MWh, respectively. These results align with expectations (e.g., [10]). $\mathrm{LCOE_{PV}}$ compares well with the cost of conventional technologies. On the contrary, $\mathrm{LCOE_{WT}}$ is much higher, highlighting criticalities in installing small-size wind turbines in the urban context [97]. The yearly energy demand is $L = 271.4$ MWh, then $E_s = 155$ MWh.

If the REC benefits from self-consumption (case 1), the LCOE of the whole REC is $\mathrm{LCOE_{REC}} = 163$ €/MWh. When the REC receives incentives for the virtually-shared energy (case 2), the LCOE for the REC is $\mathrm{LCOE_{REC}} = 228$ €/MWh. In this case, the REC is penalized by high energy purchase costs that apply to the entire electricity demand (there is no



(a)



(b)

Fig. 7. Typical daily energy flows for winter (a), and (b) summer.

self-consumption due to the simplified assumption of consumers and producers having separate connections to the distribution network). However, if we compare the global LCOE for the REC with the energy price $\overline{p}_{\mathrm{BUY}}$ we can observe that, while, in the first case, the LCOE is higher than the purchase price (the grid parity is not achieved), in the second case, the LCOE is significantly lower, highlighting the economic return for the REC users in this case.

Then, a probabilistic assessment is employed, considering the relevant parameters as random variables in the calculation of LCOE. These variables include the characteristics of the generators, the users' consumption, the discount rate, unit prices for electricity purchased and sold to the grid, incentives, and rates for self-consumed or virtually-shared energy. Mean values μ_{x_p} of each parameter are assumed equal to the nominal ones. Their coefficients of variation are taken according to the quantities reported in Table 2. The statistical relationship between $\overline{p}_{\mathrm{BUY}}$ and $\overline{p}_{\mathrm{SALE}}$ is quantified by a correlation coefficient equal to 0.92; all the other parameters are treated as independent variables.

Applying the uncertainty propagation model described in Section 3, Table 3 lists, for each parameter, the propagation coefficient, that are derived through Eqs. (13)–(31), and the related coefficient of variation of LCOE, through Eq. (12).

For checking the formulation and the role of the applied procedure, the values of $\boldsymbol{\delta}_{\mathrm{LCOE},x_k}$ were also calculated through a MC analysis. This involved generating a set of 10,000 values for each parameter, having assumed a lognormal distribution with mean and standard deviation equal to that used in the TSE analysis (Table 2). These values are used as input for Eq. (6) to calculate $\mathrm{LCOE}_{\mathrm{REC}}$. The analysis has considered one random parameter at a time, while the other ones are fixed at their mean values. The coefficients of variation obtained by the MC analyses have proven to be practically identical to the values $\delta_{\mathrm{LCOE},x_k}$ reported in Table 3, with some differences detected in the third decimal place. Besides revealing that the choice of the distribution of the input parameters has a minimal influence on the mean and standard deviation of the MC outcomes, this result shows that errors in the TSE procedure are small, and irrelevant with respect to the inherent uncertainties deriving from the lack of knowledge of the parameters. Essentially, although MC analysis is conceptually straightforward and does not require a significant computational burden, TSE enables a focus on the direct influence of the investigated quantity through direct functional relationships, rather than relying on numerical procedures.

Fig. 8(a, b) offers graphical evidence of results showing, for each input parameter, its scattering (quantified by the coefficient of variation), the propagation coefficient, and the contribution over the variability of LCOE (that is given by the product of the former quantities, according to Eq. (9)).

To give a straightforward representation of the relative importance of each variable, the tornado diagrams in Fig. 9(a, b) provide a graphical representation in terms of percentiles. These figures stem on the assumption that the distribution of $\mathrm{LCOE}_{\mathrm{REC}}$ is lognormal, with mean value and standard deviation from Table 3 (from TSE), and thus provide a qualitative representation that can be however effective in conveying the dispersion concept of the LCOE outputs associated with each uncertain input parameter. The white bars represent the values between the 15th and 85th percentiles, which cover the 70% of the data; the grey bars represent the values between the 5th and 95th percentiles, covering the 90% of the data. Parameters are sorted by increasing $\mathrm{LCOE}_{\mathrm{REC}}$

Table 2
Mean values and coefficient of variations of the input parameters.

Input parameter		
x_k	μ_{x_k}	δ_{x_k} [−]
$\mathrm{EOH}_{\mathrm{PV}}$ [h/year]	1250	0.06
$\mathrm{EOH}_{\mathrm{WT}}$ [h/year]	1314	0.50
C_{PV} [€/kW/year]	16	0.22
C_{WT} [€/kW/year]	25	0.30
d [%]	5	0.25
$\overline{p}_{\mathrm{BUY}}$ [€/MWh]	150[(1)], 250[(2)]	0.30
$\overline{p}_{\mathrm{SALE}}$ [€/MWh]	50[(1)], 80[(2)]	0.30
L [MWh]	271	0.10
ξ [−]	0.7	0.30
$\overline{p}_{\mathrm{INC}}$ [€/MWh]	118	0.10

[1] Case 1.
[2] Case 2.

Table 3
Uncertainty propagation on the $\mathrm{LCOE}_{\mathrm{REC}}$ for cases 1 and 2.

Case 1		Case 2	
c_{x_k} [−]	$\delta_{\mathrm{LCOE},x_k}$ [−]	c_{x_k} [−]	$\delta_{\mathrm{LCOE},x_k}$ [−]
−0.53	0.03	−0.52	0.03
−0.07	0.04	−0.07	0.04
−0.06	0.01	−0.04	0.01
−0.01	0.00	−0.01	0.00
−0.25	0.06	−0.18	0.05
0.40	0.12	1.10	0.33
−0.08	0.02	−0.29	0.09
0.08	0.01	0.1	0.01
−0.35	0.11	−0.3	0.06
–	–	−0.3	0.03

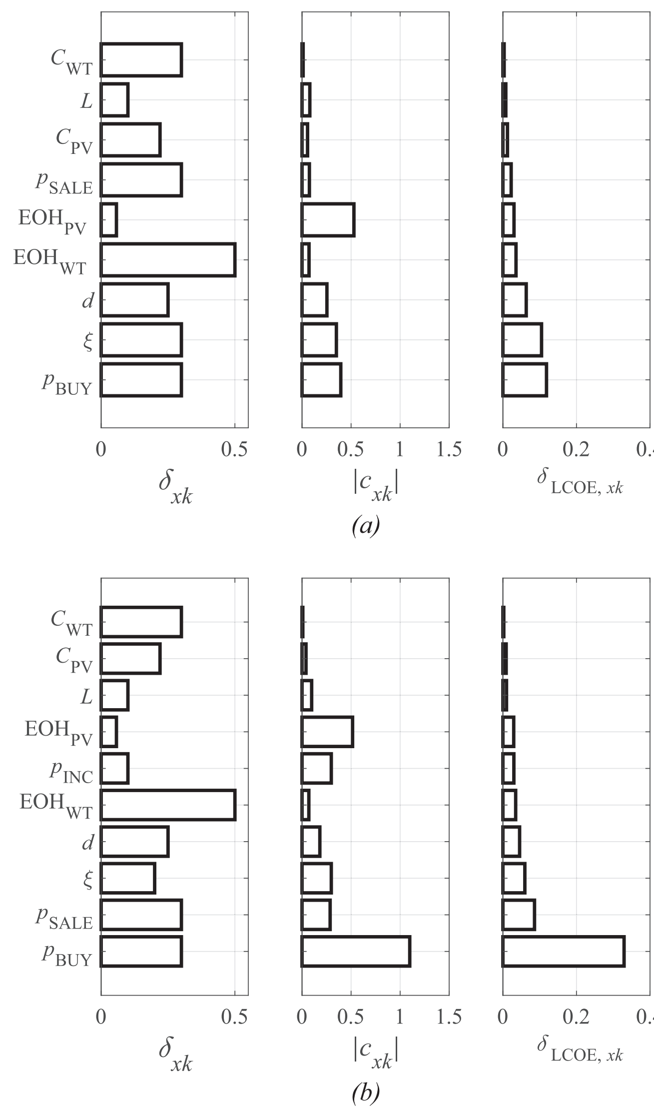


Fig. 8. Coefficient of variation, propagation coefficient for each parameter, and related coefficient of variation of LCOE for cases 1 (a) and 2 (b).

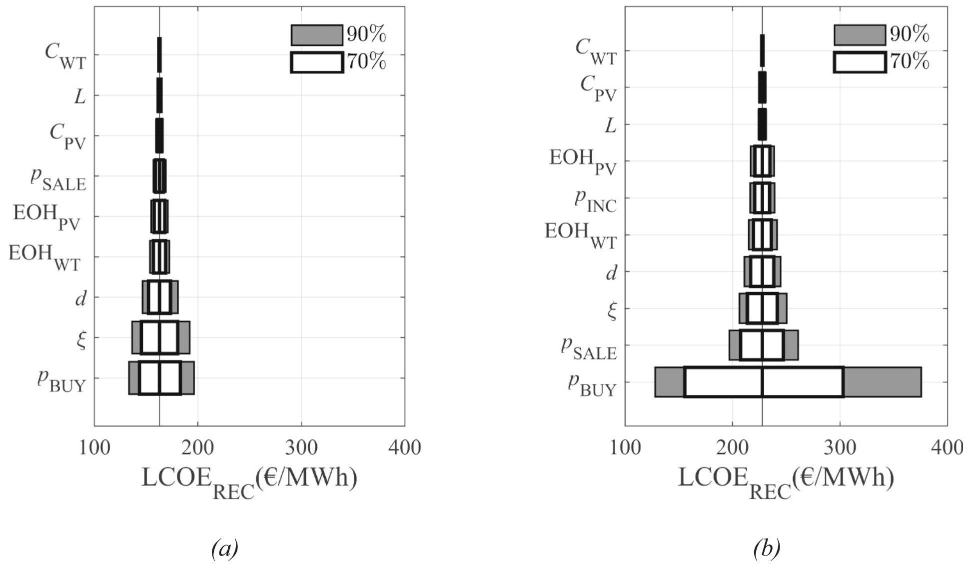


Fig. 9. Tornado diagrams for cases 1 (a) and 2 (b).

dispersion, therefore, for the ones located in the lower part of the diagram, the probable occurrences of $LCOE_{REC}$ can vary widely, encompassing shallow and very high values.

Table 3 and Fig. 9 allow appreciation of the parameters' role and their uncertainties over the resulting LCOE.

The equivalent operating hours EOH_{WT} of the WT is the most uncertain quantity (i.e., that with the largest coefficient of variation). However, being the role of wind energy production quite small, the small propagation coefficient makes its variability fairly negligible on the variability of $LCOE_{REC}$ for the considered case. Something similar happens for C_{PV} and C_{WT}, which are rather uncertain, but their propagation coefficient is small. On the other hand, the equivalent operating hours EOH_{PV} can be estimated with good reliability; notwithstanding its large propagation coefficient (i.e., it plays a large role in the energy produced by the REC), its role on the $LCOE_{REC}$ variability is also fairly negligible. Load L has a small uncertainty and quite a small propagation coefficient.

Quantities d, ξ, $\overline{p}_{SALE}$, $\overline{p}_{BUY}$ are the most responsible for the scattering of the results, characterized by rather large uncertainties and propagation coefficients. Due to the high costs of electricity in the market, $\overline{p}_{BUY}$ represents the most important quantity. However, in case 1, the self-consumed energy reduces the amount of produced energy injected and sold to the main grid, thereby mitigating the role of both $\overline{p}_{SALE}$ and $\overline{p}_{BUY}$. Conversely, in case 2, these factors gain relevance because the grid receives all the produced energy, and all the energy need is purchased from it. In this case, uncertainties associated with $\overline{p}_{BUY}$ are further amplified over the estimate of $LCOE_{REC}$ to the extent that uncertainties associated with the other parameters become almost irrelevant. Modeling this uncertainty alone is sufficient to provide a good representation of the overall scattering. Moreover, the significance of $\overline{p}_{BUY}$ would be even more pronounced if L is significantly greater than E. The role of $\overline{p}_{BUY}, \overline{p}_{SALE}$ would be reversed when L exceeds E.

When jointly considering the variability of all the parameters of the model, Eq. (9) supplies the overall coefficient of variation of $LCOE_{REC}$, $\delta_{LCOE} = 0.18$ (case 1) e $\delta_{LCOE} = 0.32$ (case 2). The correlation among $\overline{p}_{BUY}, \overline{p}_{SALE}$ slightly reduces the overall dispersion.

Fig. 10 provides some insight into the assumption of the lognormal distribution, both regarding the distribution of LCOE and with respect to Monte Carlo analyses. Referring to case 1, Fig. 10(a) reports the results of the MC simulation of $LCOE_{REC}$ where all the input quantities are distributed by a lognormal. It then reports a lognormal distribution of $LCOE_{REC}$ that uses the statistical moments from TSE considering the

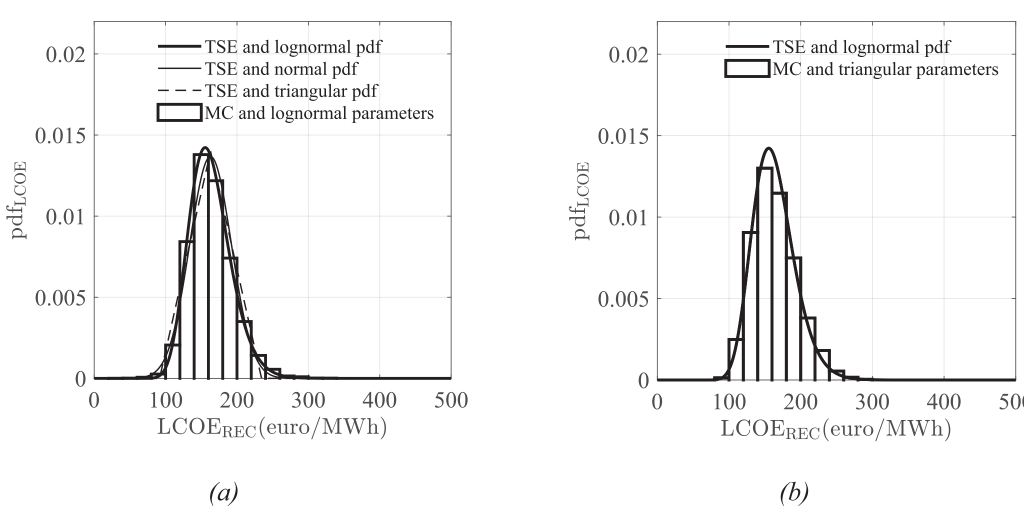


Fig. 10. Case 1, pdf from TSE assuming different distributions and MC simulation with lognormal input parameters (a), pdf from TSE assuming lognormal distribution and MC simulation with triangular input parameters (b).

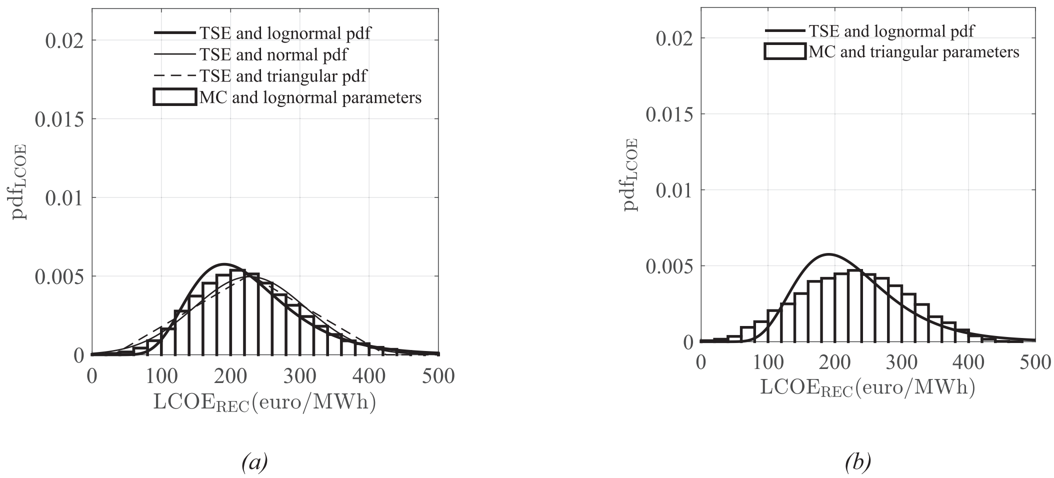


Fig. 11. Case 2, pdf from TSE assuming different distributions and MC simulation with lognormal input parameters (a), pdf from TSE assuming lognormal distribution and MC simulation with triangular input parameters (b).

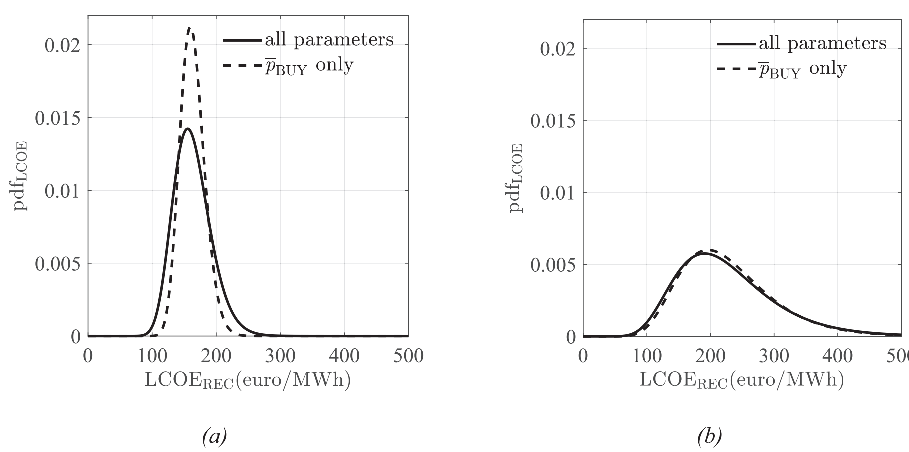


Fig. 12. Pdf of LCOE simulating all the uncertain parameters (solid line) and term $\overline{p}_{BUY}$ alone for case 1 (a) and 2 (b).

variability of the whole set of parameters. It also reports other distribution choice for LCOE$_{REC}$, respectively normal and triangular. Fig. 10 (b) reports the lognormal distribution of LCOE$_{REC}$ and the MC simulation assuming triangular distribution of the input parameters.

These diagrams suggest that, given the inevitable arbitrariness of the assumptions about the distributions, their impact does not seem to be notably significant. Indeed, in case 2, Fig. 11(a,b), for which the LCOE$_{REC}$ values are very scattered, the representation seems more influenced by the pdf of input parameters (for MC simulation) and by the distribution (based on the TSE outcomes) of the LCOE$_{REC}$ assumed. However, it remains valuable in offering an immediate visual representation of the results' scattering.

Moving on to Fig. 12, its primary focus is on the influence of the term $\overline{p}_{BUY}$ on the pdf of LCOE. The solid line represents the distributions resulting from the probabilistic modeling of the complete parameter set, while the dashed lines only consider the random variation of the term $\overline{p}_{BUY}$. Despite the significant scattering caused by the complete set of input parameters, a comparison between the solid and dashed lines indicates that the random nature of $\overline{p}_{BUY}$ has a substantial impact on the results, making uncertainties related to other quantities relatively negligible. By simulating the scattering of this specific parameter alone, a comprehensive probabilistic description is obtained, especially in case 2, closely resembling the one obtained when considering all uncertain parameters.

5. Conclusions

This paper presents an analytical model of the global Levelized Cost of Electricity (LCOE) of a REC and simplistic algebraic relations for appreciating straightforward the role of each parameter and of the uncertainties connected in its estimation. Without prejudice to the aim of obtaining a simplified metric, the methodology is proposed for comparative analyses and preliminary assessments. The formulation builds upon a previous model proposed by the authors for the global LCOE of polygeneration electrical microgrids, which encompasses multiple generation technologies and considers factors such as surplus energy compensation and incentives for the virtual-shared energy. The strength of the proposed model lies in its simplicity, enabling quick assessments while accounting for parameter uncertainties. Through Taylor Series Expansions (TSE), the authors have derived analytical expressions of the propagation coefficients, facilitating the evaluation of uncertainty propagation without the need for numerical simulations. To evaluate the accuracy of the TSE approximation, the results obtained have been compared with those derived from a Monte Carlo simulation method. The outcomes indicate very small errors, underscoring their insignificance compared to the inherent uncertainties in parameter assumptions. We would like to remark that the methodology based on analytical uncertainty propagation allows us to focus on the direct role of the quantity investigated through direct functional relationships rather than through numerical procedures. The developed procedure is robust, considering that parameters' uncertainties are mostly softened on the

LCOE of the whole REC.

Numerical results of the analyzed case studies show that the parameters that most influence the overall LCOE for the REC are the purchase price of the electricity, the yearly power load, and the self-consumption or virtual-shared energy rate. Surprisingly, despite the possible relatively high dispersion of the equivalent operating hours of solar photovoltaic or wind turbine generators, this parameter has a low impact on the LCOE scattering. In addition, the estimated low values of the OPEX of these technologies compared with the electricity purchase and sale prices makes its impact almost negligible in the dispersion of the global LCOE.

The operational context of the REC can significantly influence its performance and LCOE estimation. Under the exact same conditions (load and generation), the prices of purchased and sold electricity, as well as the inclusion of incentives, can lead to significantly different results. These factors have a direct impact on the overall economic feasibility and the achievement of grid parity, which is a crucial milestone for renewable energy projects. Then, the evaluation of the LCOE dispersion becomes particularly relevant when making decisions about the REC configuration.

The significance of acquiring statistical information for input parameters is noted as a critical challenge in implementing the proposed methodology. This paper provides a concise overview of this aspect. Therefore, a comprehensive extension of this work would necessitate a thorough investigation to gather data for all considered quantities, allowing for thorough evaluations and statistical analyses.

Other insights into future developments concern energy storage or multi-vector systems that are becoming increasingly common, paralleling the widespread adoption of renewable energy sources. Further investigations should explore the impact of incorporating energy storage devices into the LCOE formulation and its implications for uncertainty propagation,

CRediT authorship contribution statement

Luisa Pagnini: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefano Bracco:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Federico Delfino:** Supervision. **Miguel de-Simón-Martín:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Summary of equations for LCOE of a polygeneration system

In this Annex, a summary of the complete model for evaluating the global LCOE of a polygeneration system without storage devices is reported with reference to [12].

$$\mathrm{LCOE_{REC}} = \sum_{j=1}^{J}\left(f''_j \cdot \mathrm{LCOE}'_j\right) + f''^{\mathrm{GRID}}_{\mathrm{BUY}} \cdot \mathrm{LCOE_{GRID}} + \mathrm{LCOE}''_{\mathrm{SYST}} - f'^{\mathrm{GRID}}_{\mathrm{SALE}} \cdot \mathrm{LROE_{GRID}}, \tag{32}$$

where:

$$\mathrm{LCOE}'_j = \frac{\sum_{i=1}^{n_j} \frac{\mathrm{EOH}^j_i}{(1+d)^i}}{\sum_{i=1}^{n} \frac{\mathrm{EOH}^j_i}{(1+d)^i}} \cdot \mathrm{LCOE}_j + \frac{\sum_{z=1}^{\mathrm{floor}\left(\frac{n}{n_j}\right)} \left\{ \sum_{i=min\left(z\cdot n_j+1,n\right)}^{min\left[(z+1)\cdot n_j,n\right]} \left[\frac{\mathrm{C}^j_i}{(1+d)^i}\right] \right\} - \frac{\mathrm{RV}_j}{(1+d)^n}}{P_j \cdot \sum_{i=1}^{n} \frac{\mathrm{EOH}^j_i}{(1+d)^i}}. \tag{33}$$

$$\mathrm{LCOE_{GRID}} = \frac{\sum_{i=0}^{n} \frac{C_i^{\mathrm{GRID}}}{(1+d)^i}}{\sum_{i=1}^{n} \frac{(E_{\mathrm{GRID}})_i}{(1+d)^i}}. \tag{34}$$

$$\mathrm{LCOE''_{SYST}} = \frac{\sum_{i=0}^{n} \frac{C_i^{\mathrm{SYST}}}{(1+d)^i}}{\sum_{i=1}^{n} \left\{ \sum_{j=1}^{J} \left[P_j \cdot \frac{\mathrm{EOH}^j_i}{(1+d)^i} \right] + \frac{(E_{\mathrm{GRID}} - E_{\mathrm{SURPLUS}})_i}{(1+d)^i} \right\}}. \tag{35}$$

$$\mathrm{LROE_{GRID}} = \frac{\sum_{i=1}^{n} \frac{R_i^{\mathrm{GRID}}}{(1+d)^i}}{\sum_{i=1}^{n} \frac{(E_{\mathrm{SURPLUS}})_i}{(1+d)^i}}. \tag{36}$$

$$f''_j = \frac{P_j \cdot \sum_{i=1}^{n} \frac{\mathrm{EOH}_i^j}{(1+d)^i}}{\sum_{i=1}^{n} \left\{ \sum_{j=1}^{J} \left[P_j \cdot \frac{\mathrm{EOH}_i^j}{(1+d)^i} \right] + \frac{(E_{\mathrm{GRID}} - E_{\mathrm{SURPLUS}})_i}{(1+d)^i} \right\}}. \tag{37}$$

$$f''^{\mathrm{GRID}}_{\mathrm{BUY}} = \frac{\sum_{i=1}^{n} \frac{(E_{\mathrm{GRID}})_i}{(1+d)^i}}{\sum_{i=1}^{n} \left\{ \sum_{j=1}^{J} \left[P_j \cdot \frac{\mathrm{EOH}_i^j}{(1+d)^i} \right] + \frac{(E_{\mathrm{GRID}} - E_{\mathrm{SURPLUS}})_i}{(1+d)^i} \right\}}. \tag{38}$$

$$f''^{\mathrm{GRID}}_{\mathrm{SALE}} = \frac{\sum_{i=1}^{n} \frac{(E_{\mathrm{SURPLUS}})_i}{(1+d)^i}}{\sum_{i=1}^{n} \left\{ \sum_{j=1}^{J} \left[P_j \cdot \frac{\mathrm{EOH}_i^j}{(1+d)^i} \right] + \frac{(E_{\mathrm{GRID}} - E_{\mathrm{SURPLUS}})_i}{(1+d)^i} \right\}}. \tag{39}$$

In Eq. (33):

$$\mathrm{LCOE}_j = \frac{\sum_{i=0}^{n} \left[\frac{C_j^i}{(1+d)^i} \right]}{\sum_{i=1}^{n} \frac{E_j^i}{(1+d)^i}}, \tag{40}$$

the meaning of symbols is given in the nomenclature, with index j referring to the j-th power unit, index i referring to the i-th year during the lifespan of the project; n_j is the life of the j unit. In Eq. (33), RV_j refers to the residual value of the j-th asset. In Eqs. (34)–(39), E_{GRID} refers to the energy purchased to the external power grid and E_{SURPLUS} is the surplus energy sold to the grid.

Moreover, in the perspective of dealing with a further simplified application, the case is considered where the lifespan of the generators aligns with the lifespan of the overall installation, $n_j = n$. Eq. (33) simply becomes:

$$\mathrm{LCOE}'_j = \mathrm{LCOE}_j. \tag{41}$$

Appendix B. Probabilistic assessment

Let $R = g(\boldsymbol{X})$ be the function of a set of random and uncertain parameters, $\boldsymbol{X} = [x_1, x_2, \dots, x_P]$. When extensive information on $\boldsymbol{X}$ is available, it is possible to achieve a complete probabilistic description of the target function. However, this step may present some criticalities in econometric applications, as the solution is very burdensome in its general formulation. Moreover, information on the parameter distributions is usually scarce, so the user has to postulate the probability distribution of the involved quantities, and the accuracy of an entire probabilistic approach becomes questionable [109]. This fact affects numerical methods such as those based on MC simulations, as they need the distributions of the random parameters. Moreover, these procedures cannot provide an interpretative model. For this reason, analytical methods are preferable.

Expressing the function R by Taylor Series Expansion (TSE) around a nominal value of X, which is usually the mean value $\mu_X = [\mu_{x_1}, \mu_{x_2}, \dots, \mu_{x_P}]$, it derives:

$$R(\boldsymbol{X}) = R|_{\mu_X} + \sum_{p=1}^{P} \left[\left(x_p - \mu_{x_p} \right) \frac{\partial R}{\partial x_p}\bigg|_{\mu_X} \right] + \frac{1}{2} \sum_{p=1}^{P} \left[\left(x_p - \mu_{x_p} \right)^2 \frac{\partial^2 R}{\partial x_p^2}\bigg|_{\mu_X} \right] + \dots \tag{42}$$

where $\bullet|_{\mu_X}$ means the quantity is calculated considering the mean values of the parameters. Applying statistical operators to Eq. (42), one can obtain the statistical moments of R according to the information available on the statistical moments of $\boldsymbol{X}$. Keeping the first-order terms (i.e., first-order TSE), the mean value μ_R and the variance V_R of R are given by:

$$\mu_R = R|_{\mu_X}, \tag{43}$$

$$V_R = \sum_{p,q=1}^{P,Q} \frac{\partial R}{\partial x_p}\bigg|_{\mu_X} \frac{\partial R}{\partial x_q}\bigg|_{\mu_X} COV_{x_p x_q} \tag{44}$$

where $COV_{x_p x_q}$ is the covariance of x_p, x_q.

First-order TSE implies a linear approximation around the expansion point. When the parameters are scattered, the more $R(\boldsymbol{X})$ deviates from the linear approximation in the neighborhood of the expansion point, the more expressions in Eqs. (43) and (44) lose accuracy. The use of second-order terms in the TSE allows for gaining accuracy in μ_R, while it seems less remarkable in V_R [110].

Eqs. (43) and (44) supply an approximated value of the mean and variance of R as a function of the input parameters' mean and covariance. They can be solved either numerically or by symbolic calculation tools. With few parameters, TSE can be developed by closed-form solutions, giving a direct functional relationship that allows one to appreciate the contribution of each parameter. Moreover, the degree of dispersion of R can be expressed more effectively by deriving its coefficient of variation $\delta_R = \sigma_R / \mu_R$, being $\sigma_R = \sqrt{V_R}$ the standard deviation. It follows that:

$$\delta_R^2 \simeq \sum_{p,q=1}^{P,Q} D_{R,x_p,x_q}, \tag{45}$$

$$D_{R,x_p,x_q} = c_{x_p}^R \cdot c_{x_q}^R \cdot \rho_{x_p,x_q} \cdot \delta_{x_p} \cdot \delta_{x_q}, \tag{46}$$

where $c_{x_p}^R, c_{x_q}^R$ are the propagation coefficients of x_p, x_q over R, ρ_{x_p,x_q} is the correlation coefficient of x_p, x_q and δ_{x_p}, δ_{x_q} are coefficients of variation of x_p, x_q:

$$c_{x_k}^R = \frac{\mu_{x_k}}{\mu_R} \frac{\partial R}{\partial x_k}\bigg|_{\mu_X} \quad (k = p, q), \tag{47}$$

$$\rho_{x_p,x_q} = \frac{COV_{x_p x_q}}{\sigma_{x_p}\sigma_{x_q}}, \tag{48}$$

$$\delta_{x_k} = \frac{\sigma_{x_k}}{\mu_{x_k}}, (k = p, q). \tag{49}$$

When the covariance among different random parameters can be neglected, $\mathrm{COV}_{x_p x_q} = 0$ for $p \neq q$ and $\mathrm{COV}_{x_p x_p} = V_{x_p}$ is the variance of x_p.Eq. (44) simplifies to:

$$V_R \simeq \sum_{p=1}^{P} \frac{\partial R}{\partial x_p}\bigg|_{\mu_X}^2 V_{x_p} \tag{50}$$

and δ_R is supplied by the straightforward expression:

$$\delta_R^2 \simeq \sum_{p=1}^{P} \delta_{R,x_p}^2, \tag{51}$$

where:

$$\delta_{R,x_p} = \left|c_{x_p}^R\right| \cdot \delta_{x_p}. \tag{52}$$

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