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Accounting for techno-economic parameters uncertainties for robust design of remote microgrid

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ABSTRACT

This paper presents two different approaches to deal with uncertainties in the design optimization of renewable hybrid power systems in order to enhance the decision-making. The first one, Sensitivity Analysis Approach (denoted as SAA), takes the uncertainties into account after the optimization of the system. It permits first to evaluate the sensitivity on the static performances of the optimized system through uncertainty propagation. Secondly, it permits to identify the most influential uncertain parameters through Global Sensitivity Analysis (denoted as GSA). The second approach, called Robust Optimization (RO), integrates a Monte Carlo (MC) simulation into the process of optimization conducted with a Genetic Algorithm (GA). The two approaches have been set up and applied to a remote power system or microgrid, under uncertainties on techno-economic parameters. This illustrative case study is the electrical supply of a stand-alone application located in Nigeria, using photovoltaic production associated to a hybrid energy storage with a bank of batteries and a complete hydrogen chain (with an electrolyzer, a gas tank and a Fuel Cell (FC). Classically, the main source of uncertainties of such a system is associated to the temporal variation of renewable energy sources and load demands. Instead, this paper focuses on uncertainties of techno-economic parameters to improve the reliability of the optimization process for a stand-alone power system. Moreover, from a precise analysis of the state-of-the-art of such uncertainties, the authors propose to investigate complementarities of Sensitivity Analysis Approach and Robust Optimization. This study also aims to propose a methodological framework for any designer projecting to take into account uncertainties on techno-economic parameters. The results show the high interest to take into account such uncertainties for the decision-making and the ability of RO to limit their impact on system performance indicators.

1. Introduction

Nowadays, energy systems are getting more and more complex, and difficult to assess because of (i) the variability of the renewable power sources and the load demand, (ii) the resultant necessity of storage systems and hybridization and (iii) the presence of different and new energy vectors such as hydrogen [1]. Classically, these systems are designed and optimized with simulation software as Odyssey [2–4], which enables the optimization of the design and the energy management system by minimizing the cost of energy while maximizing the load satisfaction on a one-year simulation. Odyssey is a simulation-optimization platform developed by the French Alternative Energies and Atomic Energy Commission (CEA). It permits comprehensive techno-economic assessments of energy systems comprising renewable energy sources and energy storage units. The precision of the technical model is rather high, as Odyssey can for instance account for performance degradation in batteries or electrolyzer and fuel cell stacks, and components replacement during system simulation.

Besides, many parameters of any power system are uncertain, e.g. economic properties [5], static component performances [6] as well as time series of production and load profiles [7,8]. Their impacts are often evaluated by performing sensitivity computations on a limited set of key parameter variations [3,9], using simulation software like Odyssey. As a result, the impact of uncertainties will mostly be alleviated by oversizing the system to meet the demand. This obviously increases the cost of the final energy supply.

To improve the techno-economic performance of the system, it is essential to better quantify the impact of uncertainties [6,10] and make

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the system as robust as possible with respect to uncertainties [8,11]. Several methods can be used, depending on the nature of uncertain parameters. They have been applied in various contexts, but few have been exhaustively applied for techno-economic studies to such energy power systems as remote microgrid with renewable and hybridization of storage systems.

The classical uncertainty source studied in the literature for this type of system is the variability of the time series (renewable energy production and load demand). The objective is to implement existing methods to account for techno-economic uncertain parameters, which has never been done before. The methods constitute two complementary approaches: Sensitivity Analysis Approach (SAA) and Robust Optimization (RO). They highlight that these static uncertain sources have a strong impact on optimization results. Therefore, the consideration of these uncertain parameters is of high interest for decision-making. This work demonstrates also that RO can limit their impact on system performance indicators.

The quantification of sources of uncertainty is a common step of both approaches. In this work, uncertainty sources are associated to any techno-economic parameter, with a Probability Distribution Function (denoted PDF). The SAA has two distinct aims: a first propagation quantifies the impact of uncertainties on the outputs and the GSA quantifies the responsibility of each uncertain parameter in the variance of the output. The other approach, namely RO, consists in including Monte Carlo (MC) simulation in a Genetic Algorithm (GA) with an innovative optimization criteria.

These approaches have the ambition to be generic and applicable to any black box energy system simulation tool involving uncertain input parameters, in order to propose a general framework for designers. Thus, the contributions of the two approaches and the highlight of their complementarity bring new elements in the decision-making process of such systems.

A typical remote and hybrid power system is presented in Section 2. Then, Section 3 discusses the methods associated to the two approaches, namely Sensitivity Analysis Approach and Robust Optimization. Section 4 describes the application of the approaches to this remote power system. On this basis, Section 5 discusses their respective benefits and drawbacks. Lastly, Section 6 concludes and proposes some perspectives for future work.

2. Description of illustrative case study

The case study is a stand-alone power system located in Nigeria, using photovoltaic (PV) as the main power source. In order to manage the time mismatch between PV production and load requirements, at least one energy storage system is needed. A similar system was studied by Guinot et al. [3,4] and the comparison between different system architectures showed the relevance of a hybrid storage including a bank of lead-acid batteries and a complete hydrogen chain, consisting of an electrolyzer, a gas storage tank and a Fuel Cell (FC). This article focuses only on electrical power flows. This system is schematized in Fig. 1. The design of such a hybrid supply chain is particularly interesting as it implies a trade-off between two competing technologies, i.e. the battery bank and the hydrogen storage. Each component has specific technical and economic parameters, with associated levels of uncertainty. Hence, the sizing and the energy management of such a system is very likely to change according to some uncertainties.

A main DC bus connects a PV farm to an electrical load, which is to satisfy either with the PV production, or with the hybrid storage system also connected to this bus. This hybrid storage system is described Section 2.1.2.

2.1. Energy system description

The models of components describing the system are used in a black box perspective to remain independent of the particular tools used.

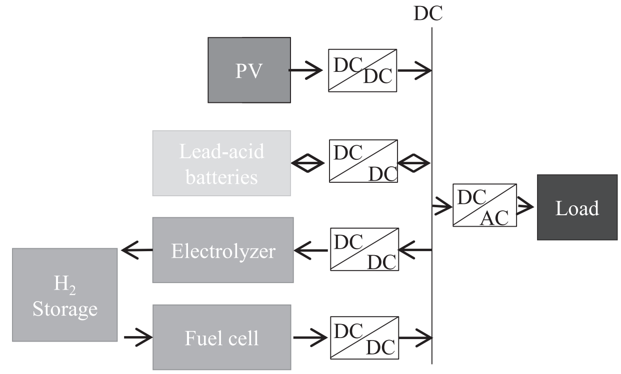

Fig. 1. Case study architecture.

Table 1
Summary of used component models in studied energy system.

Component	Model
PV	From PV production profile
Electrolyser	Polynomial I-V Curve model
H_2 tank	Pressure model with constant ambient temperature
FC	Polynomial Efficiency model
Battery bank	Efficiency model

However, the uncertain parameters contributing to the models have to be identified. Therefore, the models of components describing the system in Odyssey are listed in Table 1.

Thanks to the Odyssey simulation software, during a one year simulation, operating rules will try to satisfy the electrical load at each sampling time. If the PV production is sufficient, the exceeding power is stored in the battery (priority #1) or converted in hydrogen (priority #2). If the PV production is not sufficient to satisfy the electrical load, electrical power is requested from the battery (priority #1) or from the hydrogen supply chain (priority #2). The result of the one year simulation is then extrapolated to a 20 year-operation of the system to perform complete techno-economic analysis including discount rate of 8% and aging of components.

An external loop of optimization using Genetic Algorithm (GA) allows optimizing several key parameters as the rated power of electrolyser and fuel cell stacks, the battery capacity or the number of PV modules.

The time series of PV production, component features and energy management strategy are detailed in the following sections, along with the optimization process.

2.1.1. Load profile and photovoltaic production

The electrical load and the PV production are described with 5-min sampling time profiles with a duration of one year. These profiles are the boundary conditions, i.e. fixed inputs of the system and they will be considered as perfectly well known. The uncertainty relative to these two profiles is then not considered at this step.

The electrical load profile of the remote power system has been generated by the duplication of a daily load profile, with the application of a global random variation between −10% and +10%. The PV production profile has been calculated using global and diffuse radiations and ambient temperature measurements at Ilorin weather station in Nigeria.

2.1.2. Hybrid storage system

The hybrid storage system includes on one hand a bank of lead-acid batteries and on the other hand a complete and reversible hydrogen chain, i.e. an electrolyzer, a pressurized tank to store the produced hydrogen gas and a FC with Proton Exchange Membrane technologies for electrolyzer and FC.

The model of battery takes into account its ageing through its capacity loss [3].

The electrolyzer is modeled with its polarization curve. Its ageing model assumes a linear increase of each cell voltage with the operation time and the replacement occurs at a given amount of operating hours [12].

The produced hydrogen is stored in a pressurized tank with a maximum pressure (30 bars) equal to the output pressure of the electrolyzer; therefore no compressor is required in this application.

The FC is modeled with a polynomial model of its efficiency. Its ageing model is based on the efficiency decrease and its replacement occurs at a given amount of operating hours.

It is important to note that the models for component characterization, ageing or replacement conditions are non-linear models. This has a strong impact on the design methodology and the choice of optimization tools that can be used to evaluate and optimize the considered system. For instance, classical Stochastic Programming, that requires linear models, is not exploitable as linearization is not always obvious or even possible. That is why stochastic methods will often be applied on simplified models of the system, which do not account for precise ageing and replacement models, or even start-up or shutdown durations. These parameters must not be ignored in the case of stand-alone energy systems to get as accurate as possible the system design and operation.

2.1.3. Energy management strategy

The energy management strategy consists of classical logical rules based on the on/off switches between the electrolyzer and the Fuel Cell according to the State Of Charge (SOC) of the batteries bank. It was originally described by Ulleberg [13] and further investigated by other authors [2,14,15].

2.2. Optimization criteria and variables

Several performance indicators can be used to assess hybrid energy systems, characterizing them technically and economically. In this case study, economic performance are levelized on a 20 year-operation and with a discount rate of 8% [3]. Two performance indicators are considered as optimization criteria. The first one is the Levelized Electricity Cost (denoted LEC, in €/MWh), defined as the ratio of the total levelized cost of the system divided by the levelized amount of electricity provided to the load. The second one is a technical indicator representing how the system meets the demand: the Unmet Load (denoted UL) represents the percentage of energy based amount of unsatisfied load. The objective of the optimization is to minimize jointly these two criteria. The optimization algorithm used is inspired by the Genetic Algorithm SPEA 2 (Strength Pareto Evolutionary Algorithm 2) originally developed by Zitzler et al. [16] and implemented in the Odyssey software. Such a tool of optimization is well adapted to take into account nonlinear models of aging and replacement associated to the components of the case study.

The optimization variables are the different sizes of components. They are presented in Table 2.

Each PV module has a peak power of 1 kWp, each battery unit has a rated capacity of 10 kWh and each electrolysis cell has a maximum power of 1.95 W. The simulation software may then integrate discontinuous variables in order to take into account these rated values.

Table 2
Optimization variables (component sizes).

Variable	Unit	Optimization borders	
		Minimum	Maximum
Number of PV Modules	–	450	1700
Number of Battery Units	–	110	150
Number of electrolyzer cells	–	5	35
Fuel Cell Stack Max Power	W	2500	100000
Volume of pressure tank	m^3	1	80

2.3. Optimization results without uncertainties

Results of the optimization presented in this section, denoted as Non-Robust Optimization (NRO) are not the main point of this work but the starting point of the Sensitivity Analysis Approach (SAA). The NRO is namely part of this approach. The NRO results serve also as a comparison reference to evaluate the Robust Optimization (RO).

Due to the competition between optimization criteria as LEC and UL, the optimization results take the shape of a Pareto front as seen Fig. 2. The Pareto front is, in a multi-objective optimization, the set of solutions that are Pareto optimal, i.e. the best solution for one of the criteria. In techno-economic optimization of power systems, the LEC and the UL criteria are in competition because by increasing the component sizes and consequently the LEC, the UL is reduced and inversely.

On this Pareto front, four different design points are selected corresponding to different indicators values (LEC and UL). These points, named from their UL value, are distributed on the Pareto front, in order to study the influence of the uncertainties on the overall Pareto front. The design variables values corresponding to these four selected configurations (named hereinafter as Case 0, Case 01, Case 05 and Case 1) are given in Table 3.

These optimization results highlight a low utilization of the hydrogen chain, i.e. the components of the hydrogen chain (electrolyzer, gas storage and FC) have small optimized capacities. Indeed, the hydrogen chain is useful to reach the full autonomy; this is why its components have the biggest sizing in Case 0 in which there is no unmet load. However, this specificity has no impact on the application of the approaches presented in this paper.

Such results are very typical in Non-Robust Optimization (NRO) processes. However, they do not consider the uncertainty level associated to the input parameters. For that, two different approaches, namely Sensitivity Analysis Approach and Robust Optimization, are presented in the next sections.

3. Description of methods for uncertainty analysis

The most widespread method to assess the influence of uncertain parameters on optimization results is the parametric sensitivity analysis [9,17,18]. This approach is suitable for problems with few uncertain parameters, where various possible combinations of deterministic inputs values can be tested. This parametric sensitivity analysis can be easily applied, but brings limited information as it does not quantify the global uncertainty of the model outputs. Moreover, this approach does not quantify the responsibility of the uncertain parameters in the variability of the model output. This is exactly what the global sensitivity analysis (GSA) is intended and dedicated for [19]. The results of the GSA will be useful for instance to determine which uncertainties should be reduced or better quantified to improve the system performance or robustness. It does not directly act on the system sizing.

In order to integrate the uncertainties with the sizing of the system, the use of so-called Robust Optimization is needed.

For both approaches applied to the sizing of renewable power energy systems, the whole set of uncertain parameters is often not taken into account and the analysis of uncertainty is classically reduced to the assessment of time series [20,21]. In addition, models of uncertainties are often very basic [6,10].

This section presents the chosen methods to address these weaknesses.

3.1. Uncertainty characterization methodology

Previous efforts to assess the influence of uncertain parameters on

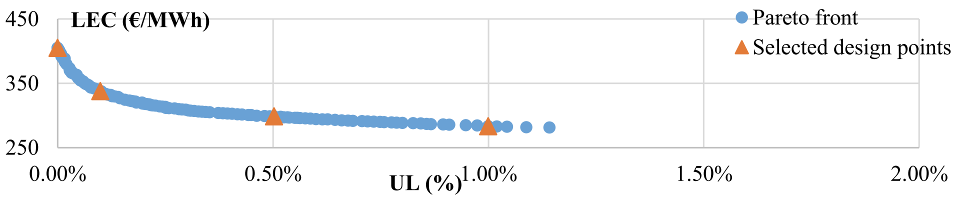

Fig. 2. Pareto front of performance indicators LEC and UL resulting from NRO.

Table 3
Selected optimal designs and their corresponding performance indicators (LEC and UL).

Case	0	01	05	1
Number of Modules PV	735	735	660	600
Number of Battery Units	146	145	135	138
Number of electrolyze cells	8	5	5	5
Fuel Cell Stack Max Power (W)	43500	10500	5000	5000
Volume of pressure tank (m^3)	31	16	3.5	3.5
Unsatisfied load (%)	0	0.1	0.5	1
LEC (€/MWh)	404.9	336.1	295.5	280.2

optimization results of renewable energy systems often do not consider the whole set of uncertain parameters. However, it is crucial to take into account all parameters in the analysis, especially the techno-economic ones [22]. Thus, as the uncertainty characterization is a common step of the two approaches studied in this article (SAA and RO), the methodology to characterize the uncertainty associated to parameters is detailed in this section.

The uncertainty is represented by a Probability Density Function (PDF) associated to the static uncertain input parameter value. Uncertainties associated to the time series are not considered in this paper.

The characterization method is described by the following steps:

1. First, a literature research is conducted to identify existing, validated or accepted uncertainty probabilistic models for the different parameters of the considered energy system.
2. If no PDF was found in the literature, a uniform law is attributed to the parameter value with minimal and maximal values deduced from the literature. The uniform law is chosen to represent the equiprobability between the parameter values.
3. The parameters for which only a rated value has been found out, i.e. the parameters for which neither a probability density function nor minimal/maximal values have been found out, are separated in two categories as suggested by Moret [22]:
   a. Parameters associated to the ageing of the component. For them, the PDF is a uniform density function, centered on the rated value, with an amplitude of 50%.
   b. Parameters not associated to any ageing, for which uncertainties are modeled with a uniform density function, centered on the nominal value, with an amplitude of 5%.

This characterization methodology permits systematic attribution of PDF to any static uncertain parameter required for SAA and RO. It is applied to the illustrative case study in Section 4.1.

3.2. Sensitivity analysis approach methodology

The Sensitivity Analysis Approach (SAA) has two aims. The first one is to quantify the impact of parameter uncertainties on the model outputs, which is realized through uncertainty propagation. The second one is to identify the most influential uncertain parameters and to quantify the influence of one uncertain parameter on the output variance, which is realized through GSA.

3.2.1. Uncertainty propagation

Once each uncertain parameter is characterized, the propagation of uncertainties allows the analysis of the change in performance indicators with respect to these uncertainties. From the probability distribution associated to each uncertain parameter, the methodology consists of a Monte Carlo (MC) propagation, i.e. the sampling of the uncertain parameters (considered as independent) and the evaluation of the corresponding design performances, calculated with the Odyssey simulation software. In this work, the MC launcher provided by the Uranie software [23] is coupled to Odyssey executable. The "Uncertainty and Sensitivity" platform Uranie developed by the CEA aims to capitalize all methods and algorithms about uncertainty and sensitivity in the same framework. Uranie is based on the data analysis framework ROOT (http://root.cern.ch), an object-oriented computing system developed at CERN.

The performance sampling sets that are obtained permit the calculation of statistical values on performances to better understand and assess the impacts of uncertainties on the outputs of the system. The statistical quantities (mean, variance, confidence interval…) or the representation of the performance distributions (with scatter plots or histograms) contribute to facilitate the decision-making process for designers and improve the confidence in the results. Some of these elements resulting from this coupling for the illustrative case study are investigated in Section 4.2.1.

3.2.2. Global sensitivity analysis

The aim of the sensitivity analysis is to identify the most influential uncertain parameters and to quantify the influence of one uncertain parameter on the output variance. In particular, the GSA considers the variability of the uncertain inputs on their whole variation domain simultaneously. GSA methods are mature, frequently improved [24] and are used in various domains as Life Cycle Assessment [25] or Building Performance Simulation [26]. In the field of power system design, Moret et al. [22] and Mavromatidis et al. [21] have used two-stage GSA to deal with a large number of uncertain parameters, for respectively national or local (i.e. at neighborhood scale) energy planning. This two-stage GSA was first proposed by Campolongo et al. [27].

First stage: factor fixing

The stage of factor fixing aims to identify non-influential parameters, i.e. uncertain input parameters that have a negligible effect on the system performance output. For that, the Morris method [28] is a relevant screening and qualitative method allowing classifying the uncertain parameters in three categories:

- parameters with negligible effect,
- parameters with linear effect and without interaction,
- parameters with nonlinear effect and/or interactions (without distinction of these two effect types). The fact that there is no distinction between the parameters with nonlinear effects and/or interactions has no consequence because the aim of this stage is only to determine the parameters with a negligible effect, in order to further focus the study on parameters with a significant effect.

The Morris method generalizes One-factor-At-a-Time (OAT) protocols and lies between local and global methods [22]. The method consists in repeating r times the OAT principle choosing randomly the starting point, building so r trajectories and calculating for each trajectory the elementary effect (EE) for each uncertain input parameter.

Considering the following mathematical framework:

$$f: \mathbb{R}^d \to \mathbb{R} \tag{1}$$

$$X \mapsto Y = f(X)$$

Y is the scalar output of the model, built with d uncertain parameters gathered in the X vector. So,

$$X = \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_d \end{pmatrix}$$

Denoting Δ_i the chosen variation in the trajectory of parameter X_i, the EE is calculated as follows:

$$EE_i = \frac{f(X_1, \cdots, X_i + \Delta_i, \cdots, X_d) - f(X_1, \cdots, X_i, \cdots, X_d)}{\Delta_i} \tag{2}$$

The major advantage of this method is its low computational requirements. In fact, the Morris method requires $N = r * (d + 1)$ code computations, with r the number of trajectories, $r \in [\![4; 10]\!]$ [19]. The approximation made by fixing non-influential factor can be calculated with a methodology presented by Sobol et al. [29].

Second stage: factor prioritization

Factor prioritization aims to rank the most influential parameters on the output variance. A quantitative appreciation of their influence can be obtained by using variance-based methods. Sobol [30] showed that variance decomposition can be obtained, if the d uncertain parameters X_i are aleatory and mutually independent and is expressed as:

$$Var[Y] = \sum_{i=1}^{d} V_i(Y) + \sum_{i<j} V_{ij}(Y) + \sum_{i<j<k} V_{ijk}(Y) + \cdots + V_{12\cdots d}(Y) \tag{3}$$

where

$$V_i(Y) = Var[\mathbb{E}(Y|X_i)] \tag{4.a}$$

$$V_{ij}(Y) = Var[\mathbb{E}(Y|X_i X_j)] - V_i(Y) - V_j(Y) \tag{4.b}$$

The sensitivity indices are:

$$S_i = \frac{Var[\mathbb{E}(Y|X_i)]}{Var(Y)} = \frac{V_i(Y)}{Var(Y)} \tag{5.a}$$

$$S_{ij} = \frac{V_{ij}(Y)}{Var(Y)} \tag{5.b}$$

$$S_{ijk} = \frac{V_{ijk}(Y)}{Var(Y)} \tag{5.c}$$

The total sensitivity indices [31] transcribe all the effects of an uncertain input on the output:

$$S_{T_i} = S_i + \sum_{j \neq i} S_{ij} + \sum_{j \neq i, k \neq i, j<k} S_{ijk} + \cdots \tag{6}$$

These sensitivity indices, denoted as "measures of importance", are ranged from 0 to 1 and are easily interpretable, what makes them very relevant among designers. They directly represent the part of the output variance that could be avoided if the parameter X_i could be fixed, i.e. if the parameter X_i would be known with certainty.

The estimation method that is used for this study is the one proposed by Saltelli [32], where the number of model evaluations is $N = n_S * (d + 2)$, with n_S the Monte Carlo sampling size.

The application of the Morris method followed by the calculation of the total sensitivity indices gives to the user the absolute and relative influence of each uncertain input parameter on the variance of the outputs. As far as hybrid energy system design is concerned, it is of strong interest as it gives a better knowledge about inherently very uncertain systems. More precisely it allows to quantify information on (i) the design risks and (ii) the uncertain input parameters playing on this risk, e.g. parameters linked to non-fully mature components. The application of the GSA results are presented in Section 4.2.2.

In this work, the presented SAA methods are applied to the static techno-economic parameters in a hybrid stand-alone power system, which has never been referenced up to now.

3.3. Robust optimization methodology

While SAA evaluates the robustness of the optimal solution a posteriori, Robust Optimization takes into account the probability distributions of uncertain parameters during the optimization process itself. It permits integrating the uncertainty of a system in its design process.

A lot of techniques exist to perform this. For instance, Zakariazadeh et al. [33], Pazouki and Haghifan [34] and Mavromatidis et al. [35] investigate a two-stage Stochastic Programming, by representing the uncertainties on time series with the use of scenarios. To surpass the need to provide the probability distribution functions of the underlying stochastic parameters, a robust approach has been proposed where the random parameters belong to uncertainty sets in Bertsimas and Sim [36]. In the energy field, Moret et al. [37] adapted and used it in Strategic Energy Planning. Recently, Maggioni et al. [38] compared these approaches with Stochastic Programming. However, this approach uses a different modeling of the uncertainty than the GSA methods cited before. This paper proposes then a comparison between two methodologies, taking into account that the modeling of the uncertainties should be the same in the two approaches. Another constraint of the Stochastic Programming is the necessity to formulate a linear model which cannot be applied in our black box simulation perspective. Moreover, this approach is not suitable for multi-objective optimization.

To deal with multi-criteria optimization using nonlinear models, metaheuristic algorithms can be used. Besides this advantage, the metaheuristic algorithms like Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) are based on the exploration of the problem variables space including randomness during the search for optimality, limiting so the number of model evaluations. By combining these methodologies with the Monte Carlo (MC) simulation, the definition domains of uncertain parameters can be explored, performing so a Robust Optimization (RO). For instance, Maleki et al. [39] uses MC simulation and PSO algorithm to optimize an off-grid hybrid renewable system taking into account the resource and load uncertainties. The combination of the GA and the MC simulation, which is compatible with a multi-criteria optimization, offers a techno-economic optimization framework in this study. It was first proposed by Cantoni et al. [40] and further investigated by Marseguerra et al. [41]. Recently, Roberts et al. [20] used it to optimize a renewable based hybrid power system considering as uncertain the time series (renewable productions and load) and the components availability. In [20], the optimization criteria are based on the worst performance indicator (worst case observed in one sample), while in our paper one of the optimization criteria measures the variability of one performance indicator during the optimization itself.

The added value of this method, in comparison to the classical genetic algorithm, is the improvement of the calculation of the optimization criteria. Instead of being direct outputs of the model, these criteria are calculated as statistical values. Fig. 3 illustrates how the proposed RO works, i.e. a GA including a MC simulation (doted arrows) in comparison to a classical genetic algorithm.

MC simulation is conventionally used to estimate the expected values of the model output with uncertainties in the renewable sources and load. However, any statistically calculable value can be used as an optimization criterion, depending on the objective of the user. The new

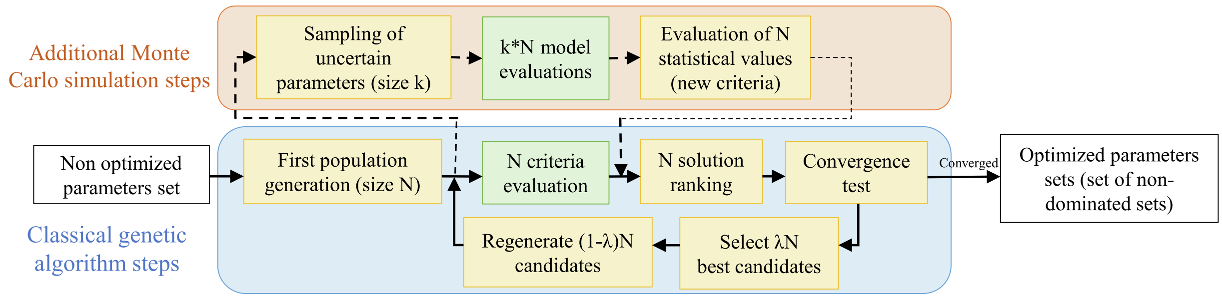

Fig. 3. Principle of the GA including MC simulation.

optimization criteria used for this work combines the mean and the variability of each performance indicator:

$$Optimization \quad Criteria = \mu + \alpha * \sigma \tag{7}$$

where μ denotes the mean of the output indicator, σ, the standard deviation and α, a non-strictly positive factor. By varying the value of α, the user can express the weighting function that the user requires between the performance and their dispersion. If the dispersion is not a critical point at all, α can be null. The more important the dispersion is, the highest should be the value of α.

With this construction of criteria, the presented RO method is suited for proposing a robust design to the uncertainties. This method gives users the opportunity to design a system considering the uncertainties while choosing the nature of their impact on the resulting performance indicators. This makes robust optimization a powerful tool as it is not always possible to reduce the uncertainty of input parameters in the field of hybrid energy system.

It seems that application of RO method to a stand-alone hybrid energy system has never been referenced up to now. In this work, we have adapted this approach and applied it on the case study (see Section 4.3).

4. Application to the illustrative case study

Neither the Sensitivity Analysis Approach nor the Robust Optimization have been applied to a stand-alone hybrid power system in order to account for the uncertainty of the static techno-economic parameters used in its modeling. In this section, the described methods are then applied to the case study presented in Section 2.

4.1. Uncertainty characterization

For most of studies on hybrid power systems, time series are the only uncertainty considered. In the present paper, we have chosen to focus on a fairly rare case study where the uncertainty sources are all the techno-economic parameters. In our case study, 24 static techno-economic inputs have then been identified as uncertain parameters. The uncertainty characterization method presented previously in paragraph 3.1 is applied and Table 4 summarizes the uncertain parameters of the system components considered in the study, with their associated PDF.

Due to the variety of the state-of-the art and the non-maturity of several system components as the hydrogen chain, the attribution of PDF is a complex exercise. However, this is an unavoidable step for the accuracy of the presented approaches [22].

4.2. Application of sensitivity analysis approach

The SAA evaluates the robustness of the optimal solution a posteriori. Thus, the different designs investigated with this approach (Case 0, Case 01, Case 05 and Case 1) arise from the NRO. In the case study, the output performance indicators are the LEC and the UL. Uncertainty propagation then evaluates their robustness and GSA identifies the most influential uncertain parameters on their variance.

4.2.1. Uncertainty propagation

For each design (Case 0, Case 01, Case 05 and Case 1) described in Section 2, the simulation is iterated for 300 Monte Carlo histories.

Fig. 4 shows the resulting performance indicators LEC and UL with the Pareto front resulting from the NRO. The scatterplots show that the considered uncertain parameters have a strong impact on the performance indicators. Several realizations have better performances (i.e. lower LEC and UL) but a lot of configurations have lower performances (i.e. higher LEC and UL) than expected. Depending on the considered design, the scatter plots do not have the same shape, as well as the histograms of Fig. 5.

The histograms of the performance indicators UL and LEC show the repartitions of the values which differ between the cases 0 and 05. The histograms obtained for design cases 01 and 1 (not shown in Fig. 5) have shapes very similar to the ones obtained for cases 0 and 05 respectively. The reference intervals of the LEC and the UL values are identified in Fig. 5 with a red star. The reference value is not necessary situated in the interval with the maximum probability to be represented (e.g. in Case 0 for UL). It shows that making a decision with only the reference value is a very risky choice.

For an optimal analysis of the results, it is interesting to highlight the confidence interval.[2] The 90% confidence interval for the UL is four times narrower for the cases 0 (and 01) than for the cases 05 (and 1). It means that case 0 will be four times more robust to uncertainties than other cases. This can be explained by the fact that these designs include oversized components for rated conditions. In cases where the uncertainties reduce the performances of the system, the oversizing limits the created unsatisfied load.

By contrast, the width of the 90% confidence interval for the LEC is smaller with the augmentation of the associated UL, i.e. the case 0 has the biggest confidence interval for the LEC and the case 1 the smallest one. This means that the design of the case 0 is the most robust to uncertainties, compared with the other designs. This can be explained with the fact that in this study, the LEC is principally linked to the investment cost of the system, which is bigger for oversized designs (cases 0 and 01) than for the other designs. So, the uncertainties on economic parameters are mostly influential on the more expensive designs, i.e. the designs of the cases 0 and 01.

The graphical representation and statistical quantities that can be calculated thanks to uncertainty propagation are then relevant and useful tools for the decision-maker.

4.2.2. Global sensitivity analysis

To go further in the analysis of the optimal configuration obtained with NRO, the GSA is also a powerful tool, applied in this paper to the design cases denoted as 0, 01, 05 and 1. It quantifies (qualitatively and quantitatively) the responsibility of the uncertainty of one uncertain

[2] The 90% confidence interval of a variable represents the interval in which the value of a variable has 90% of chance to be situated.

Table 4
Uncertain parameters and associated probability distributions (with Uniform (U), Beta (β) or Weibull (W) laws) for our case study.

Component	Parameter	Unit	PDF	Reference
PV	CAPEX	€/Wp	β [α = 1.8; β = 6; Min = 0.374; Max = 3.165]	[42]
	OPEX	% CAPEX	U [2; 10]	CEA data*
	Replacement cost	% CAPEX	U [16.5; 22.5]	[42]
	Replacement time	h	W [α = 5.3759; β = 30; Min = 0]	[43]
Electrolyser	CAPEX	€/W	U [6.5; 13.1]	CEA data*
	OPEX	% CAPEX	U [2; 10]	CEA data*
	Replacement cost	% CAPEX	U [9; 37]	[12]
	Degradation	µV/Operating h	U [0.4; 15]	[12]
	Replacement time	Operating h	U [30000; 90000]	[12]
	Cell voltage**	–	U [1.39; 1.54]	CEA data*
H_2 tank	CAPEX**	€/m^3	U [18055; 28239]	CEA data*
	OPEX	% CAPEX	U [2; 10]	CEA data*
FC	CAPEX	€/W	U [2.2; 8]	CEA data*
	OPEX	% CAPEX	U [2; 10]	CEA data*
	Replacement cost	% CAPEX	U [30; 36]	[2]
	Efficiency**	–	U [0.30; 0.34]	CEA data*
	Degradation	%/h	U [0.45; 1.35]	[44]
	Replacement time	Operating h	U [10000; 20000]	[45]
Battery bank	CAPEX	€/Wh	β [α = 1.31; β = 3.5; Min = 0.102; Max = 0.354]	[46]
	OPEX	% CAPEX	U [2; 10]	CEA data*
	Charge efficiency	–	β [α = 1; β = 4; Min = 0.8; Max = 0.9]	[32]
	Discharge efficiency	–	β [α = 1; β = 4; Min = 0.8; Max = 0.9]	[32]
	Self-discharge	W	U[3.75E-5; 1.4E-4]	[47]
	Capacity loss	Wh/h	U [1.4E-5; 4.2E-5]	[48]

CEA: French Alternative Energies and Atomic Energy Commission.
CAPEX: CAPital Expenditure.
OPEX: OPerating Expenditure.
* CEA expert interviews.

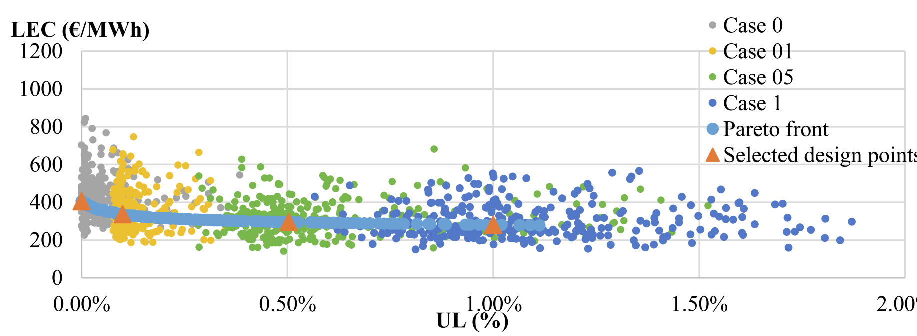

Fig. 4. Performance indicators LEC and UL for the four selected design configurations with propagation of uncertainties.

input in the variability of the performance indicators. This indicator is very useful in order to drive further investigation to gather information on the most uncertain input parameters and to make effort to reduce their dispersions.

First stage: Factor fixing

The Morris method, applied to each design case, allows to select among the uncertain parameters the one with a non-negligible influence on the output performance indicators (UL and LEC). In Table 5 the notation "+" means that the uncertain parameter has a non-negligible influence on the output, based on the Morris method, realizing the first stage (i.e. factor fixing) of the Global Sensitivity Analysis (GSA). Therefore, this uncertain parameter is kept for the rest of the second stage of the GSA (i.e. factor prioritization). On the contrary, the notation "–" means that the uncertain parameter has a negligible influence on the output. Therefore, this uncertain parameter is not kept for the rest of the second stage of the GSA.

We can observe that the eliminated parameters are not the same for LEC and UL indicators. In this work, the UL is uncorrelated from the economic parameters, so the Morris method naturally eliminates the uncertain economic parameters for the calculation of the sensitivity indices for the UL. On the contrary, the LEC is not influenced only by economic parameters, since it depends also on the electricity production. For the sensitivity indices calculation related to the LEC, the most influential uncertain technical parameters are not eliminated by the Morris method.

Second stage: factor prioritization

The normalized total sensitivity indices shown in Fig. 6 indicate the ratio of the output variance that is explained by an uncertain parameter and its interaction effects with other uncertain parameters.

Analysis of Unmet load

Considering the unmet load variance, the sensitivity indices represented in Fig. 6 indicate that the most influential uncertain parameter, whatever the case, is the capacity loss of the battery, followed by its discharge efficiency. The importance of these two parameters, both related to the battery bank, shows the major role played by this component in the load satisfaction.

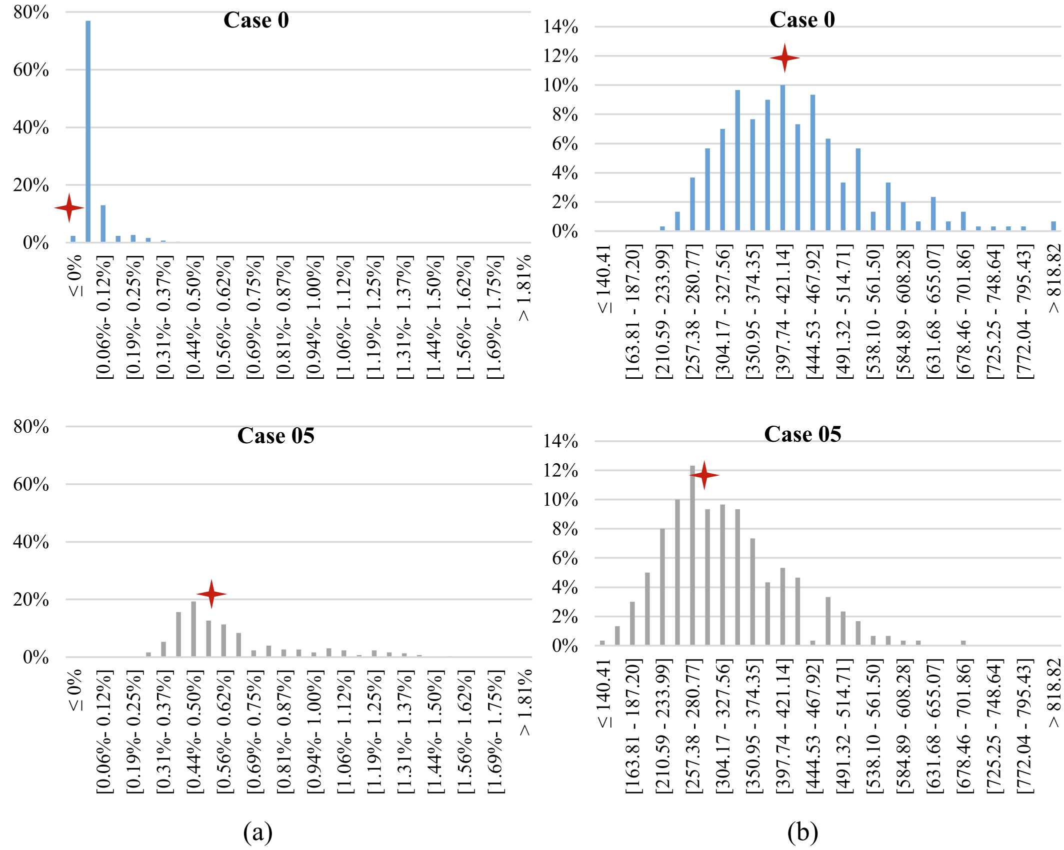

Fig. 5. Distribution after uncertainty propagation of the performance indicators UL in % (a) and LEC in €/MWh (b).

Table 5
Morris method results on the case study.

Component	Parameter	LEC	UL
PV	CAPEX	+	–
	OPEX	+	–
	Replacement cost	–	–
	Replacement time	–	–
Electrolyzer	CAPEX	+	–
	OPEX	+	–
	Replacement cost	–	–
	Degradation	–	+
	Replacement time	+	–
	Cell voltage	–	+
H_2 tank	CAPEX	+	–
	OPEX	+	–
FC	CAPEX	+	–
	OPEX	+	–
	Replacement cost	–	–
	Efficiency	–	+
	Degradation	–	+
	Replacement time	–	–
Battery bank	CAPEX	+	–
	OPEX	+	–
	Charge efficiency	+	+
	Discharge efficiency	+	+
	Self-discharge	–	+
	Capacity loss	+	+

The discharge efficiency is much more influential than the charge efficiency because, whatever the considered case, the PV farm is oversized and therefore the solar production is in excess, limiting the role of the charge efficiency. This last parameter takes a bigger importance only in cases 05 and 1, (responsibility of respectively 3 and 5% of the unmet load variance), where the PV sizing is smaller (Table 3).

The obvious ascendancy of the battery on the hydrogen chain is due to their respective sizing and associated strategy of energy management. Table 6 illustrates that the hydrogen chain (i.e. the FC) supplies a negligible electric power, even in the case 0, in which the FC has the biggest sizing (Table 3), i.e. for which the hydrogen chain is the most favorable.

This identification helps reconsider the hybrid energy system, recognise potential weaknesses that could have been neglected (e.g. battery capacity loss) or differentiate parameter with a priori similar use (e.g. charge and discharge efficiency).

Analysis of Levelized Electricity Cost

The Sobol sensitivity indices indicate that whatever the case, the most influential uncertain parameter on the LEC variance is the PV CAPEX, far ahead of the PV OPEX parameter and to a lower degree the CAPEX of the battery bank. This information is crucial because it helps understanding and managing the LEC variance, which is a central decision-tool.

The hydrogen chain plays a significant role in the LEC variance only in the case 0, i.e. with its largest design. Indeed, 26% of the total cost corresponds to the chain and especially 19% for the FC (Fig. 7).

Moreover, if the Sobol index of a given parameter is linked to the cost weight of the corresponding component (studied in Section 2), there is no direct proportional link because of the influence of the probability distribution of the input parameters values. For instance, the battery bank that plays an important role in the system cost (between 19% and 26%) has a relatively small impact (lower than 8%) on the LEC variance.

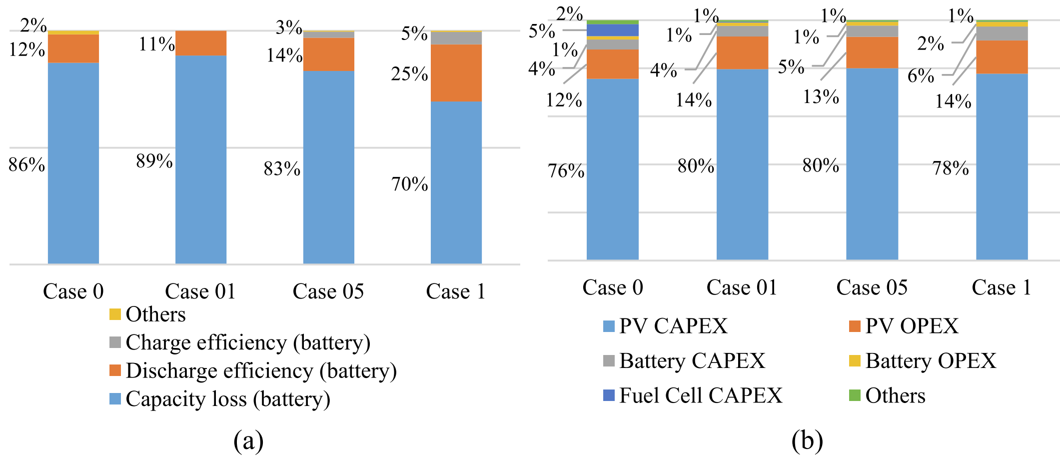

Fig. 6. Normalized Sobol indices (total order) calculated for the four selected designs, related to the UL (a) and to the LEC (b).

Table 6
Levelized total powers supplied by the hydrogen chain and the battery bank for optimal selected designs.

	Electrical storage bank DISCHARGE power (MWh)	Fuel cell stack power (MWh)
Case 0	213.92 (98%)[a]	4.09 (2%)
Case 01	210.97 (99%)	1.84 (1%)
Case 05	210.78 (99%)	1.45 (1%)
Case 1	210.89 (99%)	1.33 (1%)

[a] The percentages correspond to share of supplied power provided by the hydrogen chain and the battery bank to satisfy the load.

4.3. Robust optimization application

The application of the RO to the case study aims to minimize the LEC and the UL, but also the variability of the UL. In other words, the goal is to get a more reliable value for UL, with the risk of getting a bigger value of this indicator but also a bigger and eventually more volatile LEC value. This illustrates the potential choice for the user when designing the system, to get more or less reliability for a bigger or smaller risk of unsatisfying load.

RO has the same optimization variables and optimization borders than NRO i.e. the component sizes and their optimization borders are summarized in Table 2.

RO optimization criteria to minimize are μ_{LEC} ($\alpha = 0$) and $\mu_{UL} + \alpha * \sigma_{UL}$ ($\alpha = 2.92$), calculated thanks to MC simulation. The α value of 2.92 has been calculated so that the mean value and the standard deviation have the same weight (see Eq. (8)). For that, the mean values (μ_i) and the standard deviations (σ_i) of the UL have been calculated for each selected design point (cases 0, 01, 05 and 1) after the uncertainty propagation (NRO).The coefficient α is then adapted in order to balance the Eq. (8):

$$\sum_{1}^{4} \mu_i = \alpha * \sum_{1}^{4} \sigma_i \tag{8}$$

The technical characteristics of the performed robust optimization are given in Fig. 8. This optimization has been performed on 34 threads on an Intel$^{(R)}$ Core$^{(TM)}$ i7-7700 CPU processor.

The RO results take the shape of a Pareto front whose points correspond to pairs of optimization criteria μ_{LEC} (Eq. (7) with $\alpha = 0$) and $\mu_{UL} + \alpha * \sigma_{UL}$ (Eq. (7) with $\alpha = 2.92$) for optimized design of the system. For each of these designs, the system is re-evaluated with the set of nominal values for the uncertain parameters, in order to obtain the performance indicators UL and LEC for the robust-optimized designs. The nominal values of the uncertain parameters are values used in the NRO of the classical approach. Fig. 9 shows the resulting UL and LEC pairs (RO optimal designs), on the same chart than the Pareto front resulting from the NRO. It shows that the performances are comparable but the associated designs obtained with the NRO and with the RO change, in other words that different designs lead to the same performance indicators, but not necessary with the same level of robustness. The LEC indicators arisen from RO are higher than LEC from NRO for high autonomous manner, i.e. when UL is close to 0.

To compare the results, the designs resulting from RO with similar UL performance than the NRO reference cases are selected (triangles and squares in Fig. 9). The designs corresponding to the UL 0%, 0.1%,

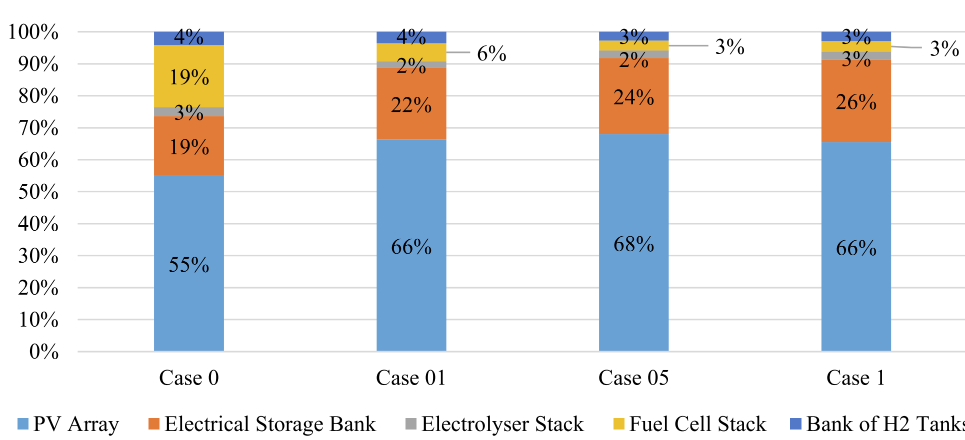

Fig. 7. Cost distributions for the four selected designs.

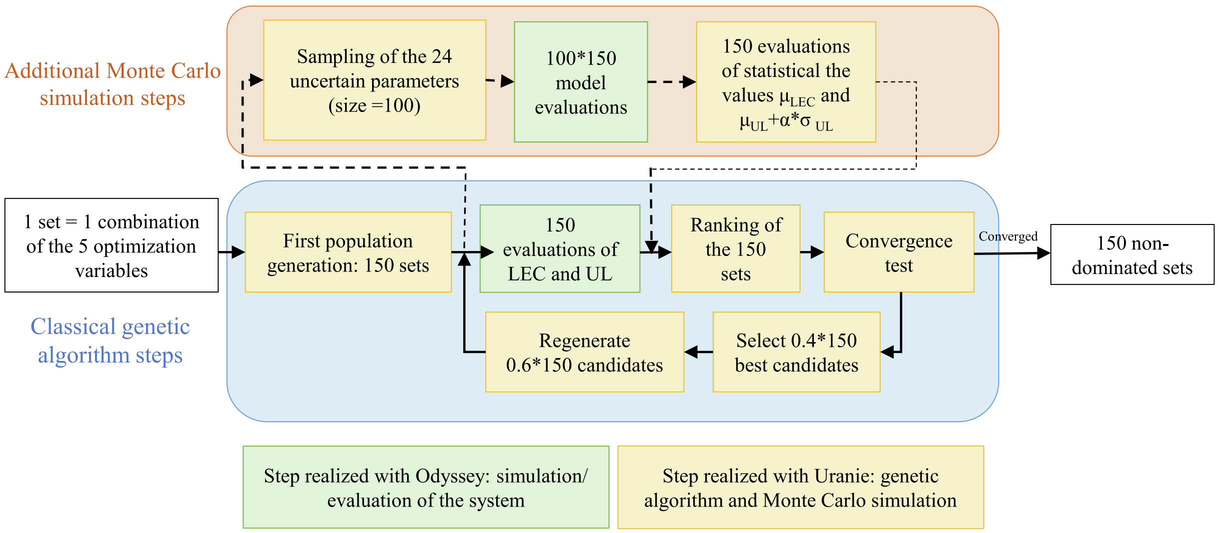

Fig. 8. Application of the robust optimization principle to the case study.

0.5% and 1% are detailed in Table 7.

The main differences are related to the sizes of the PV farm and the battery bank. In fact, to achieve the same UL, except for the case 0, the robust optimization proposes designs with a smaller number of PV modules than those resulting from the NRO. The RO always maximizes the number of battery units, reaching the upper limit defined at the beginning of the optimization, which is never the case of the NRO. The sizing of each component of the hydrogen chain resulting from the RO, does not have a clear different conclusion with the NRO. This means that for a better reliability of the UL, the best trade-off consists in increasing the battery size and not the hydrogen chain or the PV farm. The oversizing to limit the impact of uncertainties is therefore well quantified for the designer.

To evaluate if the proposed designs are more robust than the ones arising from the classical optimization, a new uncertainty propagation is performed. The mean values and the standard deviations of the LEC and UL indicators are then calculated and compared (see Table 8) with the corresponding ones resulting from the NRO as:

$$Comparison(\%) = \frac{\sigma_{RO} - \sigma_{NRO}}{\sigma_{NRO}}$$

This table confirms that robust optimization reduces the mean and the variance of the output indicators, without changing the probability distribution of the uncertain input parameters. In Table 8, the UL variance is reduced for any considered UL level (cases 0, 01, 05 and 1), as expected because it was part of its objective functions.

Additionally, this reduction has consequences on the other statistical values, as for the case 0. In fact, the increase of robustness of the UL has a strong impact on the LEC whose mean value and standard deviation increase. Indeed, to increase the robustness of the UL and reach the autonomy, the sizes of the components (PV installation and battery bank) are increased. As a first consequence, the LEC increases – which can be observed by the growth of its mean value. As a second consequence the LEC variance increases, because each variation on economic parameters has a stronger impact. However, this evolution is specific to the design obtained to provide a complete satisfaction of the load. For any other design, the performances of the robust design have similar mean value and a lower variability. Focusing to the case 1, illustrated in Fig. 10, with a small increase of the LEC, the load satisfaction and its robustness can be improved as μ_{UL} and σ_{UL} decrease.

As illustrated in Fig. 10, RO succeeds in designing a system taking into account the uncertainties, while limiting their impact on the system performance indicators (UL and LEC).

RO application to the case study permits also to propose targeted oversizing (mainly about the battery size), leading to a more robust design.

5. Discussion: Respective contributions of the two approaches

Finally, SAA and RO both include the modeling of the system and rely on the uncertainty quantification, which cannot be avoided. These approaches bring results of heterogeneous nature: namely SAA proposes statistical values on output results and responsibility shares of uncertain input parameters in their variability, while RO furnish set of

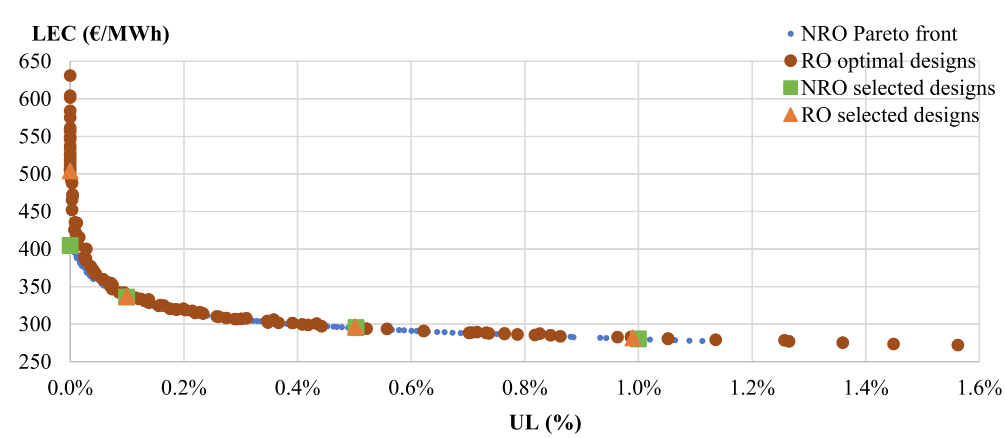

Fig. 9. Performance indicators (LEC and UL) for optimal designs resulting from RO and NRO.

Table 7
Selected optimal designs and their performance indicators LEC and UL for RO and NRO.

UL (selection performance indicator)	0%		0,1%		0,5%		1%	
Optimization	NRO	RO	NRO	RO	NRO	RO	NRO	RO
Number of Modules PV	735	1081	735	726	660	637	600	586
Number of Battery Units	146	150	145	150	135	150	138	150
Number of electrolyze cells	8	5	5	5	5	6	5	5
Fuel Cell Stack Max Power (W)	43500	42306	10500	9866	5000	2779	5000	2618
Volume of pressure tank (m^3)	31	25	16	19	3.5	3	3.5	8
Resulting LEC (€/MWh)	404.9	504.2	336.1	337.1	295.5	296.6	280.2	281.8

Table 8
Comparison of the performance indicators (mean values and standard deviations) between RO and NRO.

		UL	LEC
Mean	Case 0	−95%	+22%
	Case 01	−10%	NE
	Case 05	−14%	NE
	Case 1	−4%	NE
Standard deviation	Case 0	−95%	+39%
	Case 01	−38%	−1%
	Case 05	−56%	−4%
	Case 1	−31%	−2%

NE: Negligible Evolution, i.e. < 1%.

optimization variables. They provide complementary information for decision-making for robust design of remote microgrid.

However, SAA has no feedback on the optimization process. It mainly brings information on the following points of interest: (i) what is the impact of the uncertain parameters on the performance indicators of one system? (ii) Which of these uncertain parameters are the most relevant to be better known to reduce this impact?

First, the uncertainty propagation step of the SAA allows the user to estimate the variability of the performance indicators with their ranges and distributions. In comparison, the classical approach, i.e. the consideration of the parameters uncertainty only taking into account their range of variations (i.e. without proper uncertainty quantification step) can provide only the variation ranges of the performance indicators.

Secondly, GSA allows identification of the most influential uncertain parameters on the performance indicators of the system. In our case study, it turns out that that they are the battery capacity loss for the UL and the PV CAPEX for the LEC. Therefore, if we propose to reduce by 50% the uncertainty of these two parameters, the variance of the UL and the LEC should be consequently reduced after a new uncertainty propagation on the same system designs.

The theoretical uncertainty reduction is the division of the probability law support intervals by two but keeping the same shape of distribution and the same mean value. The resulting new PDF are expressed in Table 9.

To evaluate the impact of the PDF modification, a new uncertainty propagation is performed. The standard deviations are calculated and compared (see Table 10) with the corresponding ones resulting from the initial uncertainty propagation with the same formula than in Table 8.

For UL and LEC, the variability is much reduced playing on only the PDF of two uncertain parameters. For the UL, the reduction of the standard deviation evolves like the Sobol sensitivity index representative for the battery capacity loss: the impact of the PDF change is the biggest for the design where the Sobol index value is the biggest (case 01).

This uncertainty propagation shows that the sensitivity analysis helped identifying the key parameters that the user has to know more accurately in order to reduce the variability of the output. In the case study, the standard deviations of performance indicator are reduced from nearly 40% for the LEC and around a half for the UL, by reducing the uncertainty on only two uncertain parameters. In practice, such an information can be very profitable in order to drive further investigation to gather information on the most uncertain input parameters and to make effort to reduce their dispersions.

RO is not suited for the same use: the SAA indicates to the user on which uncertain parameters the focus would be the most interesting, whereas the RO has a practical feedback on the design optimization process. This second approach duly notes that the knowing level cannot always be improved and favor more reliable component. As illustrated in Section 4.3, RO permits to limit the uncertainty on a targeted model output.

Due to their different natures, the two approaches meet different difficulties and limitations.

SAA brings a better knowledge on the uncertainty impact and allows us to identify the key parameters, but it has no practical impact on the system optimization results. The most practical development of this method is then to improve the uncertainty quantification. This improvement is not always possible, in particular when dealing with non-

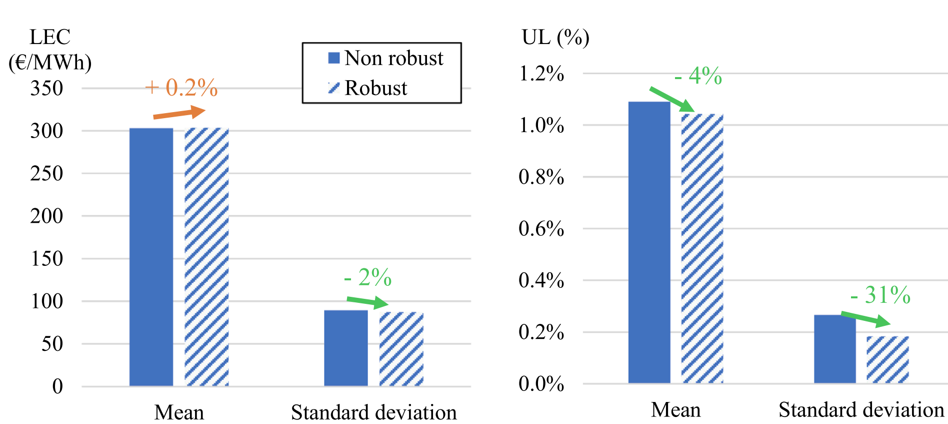

Fig. 10. Comparison for the case 1 of mean value and standard deviation of UL and LEC between the robust and the non-robust designs.

Table 9
Changes of PDF of the most influential parameters identified by the sensitivity analysis.

Uncertain parameter	Initial PDF	New PDF
Battery capacity loss	U [1.4E−5; 4.2E−5]	U [2.1E−5; 3.5E−5]
PV CAPEX	β [α = 1.8; β = 6; Min = 0.374; Max = 3.165]	β [α = 1.8; β = 6; Min = 0.687; Max = 2.0825]

Table 10
Comparison of standard deviations of performance indicators (LEC and UL) changing the laws of two parameters identified by the sensitivity analysis.

		UL	LEC
Standard deviation	Case 0	−67.2%	−38.9%
	Case 01	−67.8%	−38.4%
	Case 05	−54.6%	−37.6%
	Case 1	−41.3%	−39.6%

fully mature components, as it is often the case in modern hybrid energy systems with new sustainable technologies.

The main limitation of RO is that it requires significant computational resources and/or time. In fact 34 CPU-threads has allowed us to perform the 618000 model evaluations needed in RO in 33 hours in this case study. This important number of model evaluations is due to GA parameterization and convergence speed. GA parameterization population is settled by the population size of the GA and the sampling size of the MC simulation. Convergence speed is fixed by the number of generations needed to converge, which is not decided by the user but imposed by the algorithm. For the same optimization problem, this number of generations is much more important for RO than for NRO. So, as Roberts et al. [20] remarked, when the computational resources or time are limited, other approaches can be better adapted.

Another limitation of RO is that it does not necessary reduce the impact of the uncertainty on all the performance indicators of the system but it orients the kind of impact of the uncertainty on the targeted ones. In this work, the variability of UL is reduced, at the price to increase slightly the LEC. It means that the user must accept to let other outputs be deteriorated in order to improve the robustness of some particular ones. This is why in this kind of approach, uncertainty propagation is still required, not only to measure the improvements of the design, but also to estimate potential losses created by RO.

6. Conclusion and perspectives

This work shows how techno-economic uncertain parameters can be taken into account for designing remote power systems using two approaches: Sensitivity Analysis Approach and Robust Optimization. To take into account these uncertainties in a decision-making process, these complementary approaches are implemented and applied, considering economic and technical parameters of the model as sources of uncertainty.

Both approaches start with the inventory of all the techno-economic uncertain parameters of the system. The next shared step to the two approaches is the uncertainty quantification which consists of the attribution of a probability distribution function to each uncertain parameter value. Both also include the modeling of the system, which has been considered here as available thanks to the Odyssey software. The sensitivity analysis approach then uses the result of the non-robust optimization; from the selected designs picked out from the Pareto front. The uncertainties are propagated and a two-stage GSA is performed. Both these steps are implemented through the coupling between Odyssey and Uranie software. This approach brings information on the impact of the uncertainties on the output of the system results and identifies the most influential uncertain parameters in the output dispersion. As for RO, performed thanks to the combination of a GA and MC simulations, this second approach permits to orient the kind of impact of the uncertainty to improve the robustness of chosen performance indicators. The difference of nature of these two approaches constitutes their complementary. In fact, they bring different type of results for different needs of the user: the sensitivity analysis approach performed after the optimization gives key information on system parameters that can be used in RO.

The applicability of these existing methods is demonstrated on our case study. The two compared approaches are illustrated on the design optimization of the electrical feeding of a stand-alone application located in Nigeria, using PV as the main power source. The GSA teaches us that the most influential uncertain parameter in the UL dispersion is the battery capacity loss and the most influential uncertain parameter in the LEC dispersion is the PV CAPEX. The robust optimization is carried out with the objectives to reduce LEC and UL globally and the dispersion of UL. The obtained configurations are evaluated through uncertainty propagation: it reveals the ability of RO to find optimized configurations responding to targeted robustness criteria. The presented approaches can be applied to any other energy system design, in order to improve the decision-making regarding to the uncertainty impact on it.

Regarding future work, several perspectives are considered. First, the GSA and RO could be used including uncertainties on the renewable production resource or energy demand patterns. Next, the contribution of SAA is very useful to reduce the security margins implied by RO, which are expensive. It would be an interesting further work to quantify the avoided over-design of capacities thanks to GSA-targeted uncertainty-source reduction. Finally, the optimization of the operation of the system, complementary to the optimization of its design is also a considered improvement of this work.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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