UNCERTAINTY SENSITIVITY ASSESSMENT ON THE OPTIMIZATION OF THE DESIGN OF COMPLEX ENERGY SYSTEMS: TWO COMPLEMENTARY APPROACHES

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ABSTRACT

This paper proposes two different methods to deal with uncertainties in the design optimization of a renewable hybrid power system in order to enhance the decision-making. The first method considers the uncertainties after the optimization of the system. It permits to evaluate the impact of the uncertainties on the performances of the optimized system and through global sensitivity analysis to identify the most influential uncertain parameters. The second method integrates a Monte Carlo simulation in the optimization algorithm, allowing so to perform a robust optimization. Considered uncertainties include technical and economical parameters. These methods are applied to the electrical supply of a stand-alone application located in Nigeria, using PV as the main power source and including a hybrid energy storage: a batteries bank and a hydrogen chain (electrolyser, gas storage and fuel cell). The two methods are complementary and constitute a useful decision-making tool for dimensioning energy systems.

INTRODUCTION

Energy systems are getting more and more complex, and difficult to assess because of (i) the variability of the renewable power sources and of the demand, (ii) the resultant necessity of storage and (iii) the presence of different and new energy vectors. The modelling and simulation software Odyssey [1] enables the realization of techno-economic optimizations of such energy systems design and operation. However, many parameters used to simulate the systems are uncertain (e.g. static component performances or economic properties, but also time series of production or load profiles). To fully support decision-making about these systems, it is necessary to assess the impact of these uncertainties on the design and operation arising from the optimization process.

Up to now, techno-economic studies carried out with Odyssey, as with most other similar simulation tools, have not taken into account uncertainties, but only have provided sensitivity analysis on uncertain key input parameters. Thus, the objective of our work is to develop a comprehensive approach to enhance the design approach with capacities of uncertainty management, from the identification of the main sources of uncertainty to results analysis and to support decision-making.

We identified two main ways to account for the uncertainty influence on the results of a techno-economic optimization. The first one consists in optimizing the system and then apply the uncertainties to evaluate the sensitivity of this optimized design to uncertainties. The second way consists in optimizing the system taking directly into account the uncertain parameters to get results robust to the considered uncertainties.

These methodologies are applied to a case study consisting in the techno-economic sizing optimization of a stand-alone power system in Nigeria described in the next part.

CASE STUDY

Case study description

The case study investigated in this paper is a stand-alone power system located in Nigeria. It includes:
- an electrical load,
- a photovoltaic (PV) plant,
- a bank of Lead-acid batteries,
- a hydrogen chain made of: a PEM electrolyser, a pressurized tank to store the hydrogen and a PEM fuel cell.

This example is representative of (i) the operating competition occurring between batteries and a hydrogen chain, (ii) the issue of energy storage in off-grid power-system, and (iii) the PV over-sizing linked to the load satisfaction seeking.

The implemented power management strategy is based on the on/off switches of the electrolyser and the fuel cell; it was originally described by Ulleberg [2] and exploited on a similar case by Guinot et al. [1].

Optimization criteria and variables

The operation parameters are considered constant during the whole simulation and exploitation time. We select as optimization variables the five dimensioning variables shown in Table 1.

Table 1. Optimization variables

Variable	Optimization borders	
	Minimum	Maximum
Number of PV Modules* (-)	1	No
Number of Battery Units** (-)	1	150
Number of electrolyze cells (-)	5	No
Fuel Cell Stack Max Power (W)	1	No
Volume of pressure tank (m^3)	1	No

* Each module has a peak power of 1 kWp.
** Each unit has a rated capacity of 10 kWh.

Table 2. Selected optimized designs and their performance indicators

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

The multicriteria optimization process implemented in Odyssey uses a genetic algorithm, the Strength Pareto Evolutionary Algorithm 2 [3], in order to minimize the standard Levelized Electricity Cost (LEC) in €/MWh while minimizing the unsatisfied load (UL) in %, i.e. the energy based percentage of unmet electrical load. Therefore, two objective functions are in competition. Indeed, it is often observed that lowering the load satisfaction, by reducing the storage system size for example, leads to a lower cost of the system and thus the cost of the produced electricity. While on the contrary, improving the satisfaction of the load by oversizing the system tends to increase the cost of the produced electricity.

Optimization results

Due to the competition between both optimization criteria LEC and UL, the optimization results take the shape of a Pareto front as in Figure 1. In order to further analyze these results, four different design points were selected on this Pareto front, corresponding to different indicators values (LEC and UL). We selected the points according to the UL and we defined four different cases named from their UL value and with the designs given in Table 2. These points are distributed on the Pareto front, so that we can study the influence of the uncertainties on the overall Pareto front.
This part describes the way we identify and select the optimal system designs without uncertainty consideration. In the following, we first characterize the relevant uncertain parameters and assess their influence on the selected cases (optimized without uncertainties) and through them on the Pareto front and, then perform a robust optimization of the same energy system to compare the contribution of the two methodologies.

UNCERTAINTY CHARACTERIZATION

In the described energy system, 24 static parametrical uncertain parameters are identified. They have an epistemic nature [4].
An extensive literature research ([5], [6], [7], [8], [9]) is carried out to identify existing, validated or accepted uncertainty probabilistic models for the components of the considered energy system. The parameters for which only a nominal value could be found out, i.e. the parameters for which no probability density function could be found out, are separated in two categories: the parameters linked to the ageing of the component and the other parameters, as suggested by [10]. The probability density function attributed to the ageing parameters is a uniform density function, centred on the nominal value, with an amplitude of 50%. The probability density function attributed to the other parameters is a uniform density function, centred on the nominal value, with an amplitude of 5%. These values arise from expert interviews.

UNCERTAINTY PROPAGATION AND SENSIVITY ANALYSIS

Uncertainty propagation

The propagation of uncertainties allows to see how the performance indicators of the model respond to the uncertainties. In this study, the propagation is achieved by coupling a Monte Carlo launcher provided by the Uranie software [11] and the executable Odyssey. This simulation is iterated for 300 Monte Carlo histories. The immediate effect of the uncertainties on the performance indicators is represented in Figure 1.

Sensitivity analysis

The aim of the sensitivity analysis is to identify the most influential parameters on the output variance, in our case the performance indicators LEC and UL. A two-stage sensitivity analysis is performed in order to deal with the big number of identified uncertain parameters.
The first stage is the factor fixing, which aims at identifying non-influential parameters. It is achieved with the Morris method [12].
The second stage is the factor prioritization, which aims at ranking the most influential parameters on the output variance. To this aim, the Sobol sensitivity indexes [13] have been calculated. These indexes, denoted as "measures of importance", are included between 0 and 1 and are easily interpretable because they represent directly the part of the output variance that could be avoided if one parameter could be set to a fixed and known value.

Figure 1. Pareto front and LEC and UL indicators for the four selected design configurations with uncertainties.

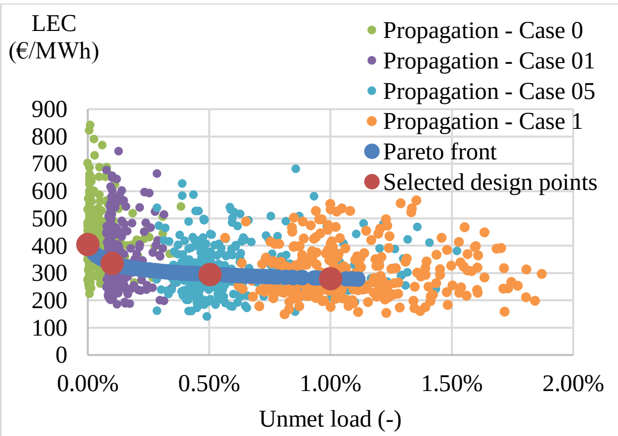
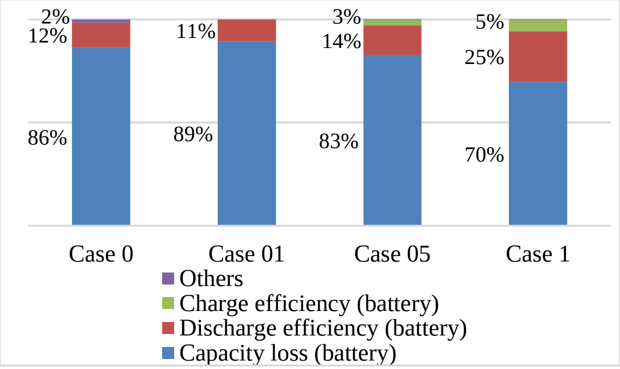


Figure 2. Normalized Sobol indexes for the four different cases, related to the UL.



The results of the two-stage sensitivity analysis (sensitivity indexes calculated after elimination of non-influential parameters) are presented in Figures 2 and 4.

Considering the UL variance, the Sobol indexes indicate that the most influencing uncertain parameter, whatever the case, is the capacity loss of the battery, followed by the discharge efficiency of the battery. The importance of these two parameters, linked to the battery bank, shows the major role played by this component in the load satisfaction. The discharge efficiency is much more influential than the charge efficiency, because the PV panel installation is oversized and therefore the electric solar production is in excess, limiting the role of the charge efficiency. The charge efficiency takes a bigger importance only in Case 05 and Case 1 (responsible for respectively 3 and 5% of the UL variance) where the PV panel installation size is smaller (Table 2).
The ascendancy of the battery on the hydrogen chain is due to their designs and control. The hydrogen fuel cell supplies a negligible electrical power compared to that delivered by the battery, even in Case 0, in which the fuel cell is designed at its largest size, i.e. when the hydrogen chain production is the most favorable.

The Sobol indexes indicate that whatever the case, the most influential uncertain parameter on the LEC variance is the PV CAPEX, far before the PV OPEX and to a lower degree the battery bank CAPEX.

Figure 3. Cost distributions for the four different cases

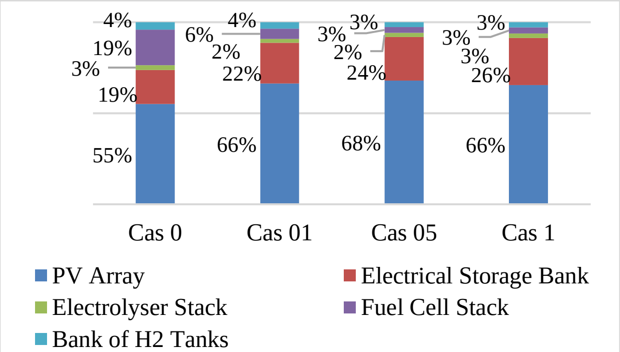
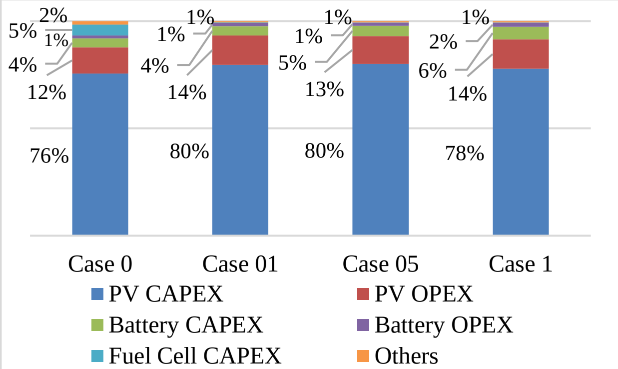


Figure 4. Normalized Sobol indexes for the four different cases, related to the LEC.



We can observe that if the Sobol index of a given parameter is linked to the cost weight of the corresponding component (Figure 3), there is however no direct proportional relation, because of the influence of the probability distribution of the input parameters values. For instance, the battery bank plays an important role in the system cost (between 19% and 26%) but has a relatively small impact (less than 8%) on the LEC variance. On the contrary, the PV panel installation (CAPEX and OPEX unified) represents the overwhelmingly part (between 88% and 94%) of the LEC variance cause while it only accounts for maximal 68% of the system cost.

ROBUST OPTIMIZATION

The other approach to reduce the uncertainty of the output is to optimize the system design by taking directly into account the uncertain parameters probability distributions in the optimization process, instead of evaluating a posteriori the robustness of the optimal solution.
The robust optimization method was first proposed by [14] and further investigated by [15]. It is the adaptation of a genetic optimization algorithm, including a Monte Carlo (MC) simulation. This method combines both (i) the exploration of the uncertain parameters definition domain (via the MC simulation) and (ii) a limited number of model evaluations thanks to the genetic algorithm. Moreover, this method is compatible with a multi-criteria optimization, necessary in the techno-economic optimization framework of this study.

Optimization criteria and variables

The optimization criteria, instead of being direct outputs of the model are statistical values, calculated from a sample of outputs. The statistical values considered as optimization criteria are designed depending on the objective of the user. In our case, the optimization criteria are expressed under the following general form:

$$\text{Optimization Criteria} = m + \alpha * \sigma \qquad \text{Equation 1}$$

In Equation 1, m is the mean of the output sample, σ the standard deviation and α is a non-strictly positive factor, permitting to express the ponderation that the user chooses between the performances and the dispersions of the performances.

In this study two robust optimizations (RO), based on different criteria, are tested and then compared to the non-robust optimization:

- RO1: the objective functions are to minimize the mean of the LEC and the mean of the UL. The outputs dispersions resulting from the uncertainties is not taken into account, i.e. $\alpha = 0$ for the objective function associated to UL and for the optimization criterion associated to the LEC.
- RO2: for the LEC, the objective function remains the mean (as in RO1). On the contrary, the objective function associated to the UL includes the mean and the dispersion. Both have to be minimized. In other words, the goal is to get a surer UL, at the risk of getting a bigger UL. So it means $\alpha > 0$ for the objective function associated to UL and $\alpha = 0$ for the optimization criterion associated to the LEC

The optimization variables are the same as in the non-robust optimization (see Table 1).

Optimization results and comparison with the non-robust optimization

The two different robust optimizations (RO) and the non-robust optimization (NRO) lead to different results, i.e. different optimal designs. To compare these results, the designs resulting from RO1 and RO2 with similar UL performance are selected.

The main differences come from the sizing of the PV installation and of the battery bank. In fact, to achieve the same UL, except for Case 0, both robust optimizations propose designs with a smaller number of PV modules than that resulting from the NRO. The robust optimizations almost always maximize (only one minimal exception for RO1, Case 01) the number of battery units, reaching the optimization superior border, which is not the case of the NRO. The designs of the components of the hydrogen chain resulting of robust optimizations do not have a clear difference tendency with the NRO.

To compare RO results with NRO results, the mean and the variance are calculated after a new uncertainty propagation on the system designs resulting from the RO. They are compared with the corresponding statistical values resulting from the NRO with the formula:

$$Comparison\ (\%) = \frac{V_{RO} - V_{NRO}}{V_{NRO}} \quad \text{Equation 2}$$

Except for the negligible evolutions (i.e. $\leq$ 1%), the only positive evolutions are the statistical values (mean and variance) for LEC in Case 0. All the other evolutions are negative, i.e. in all other cases the mean and the variance are reduced by the RO method in comparison with the NRO.

Thus, the robust optimizations permit to reduce the mean and the variance of the output indicators, without requiring any additional specification of the probability distribution of the uncertain input parameters. The UL variance can be reduced for every UL level considered (cases 0, 01, 05 and 1) in RO1 and RO2.

Nevertheless, this reduction has consequences on the other statistical values, and in Case 0 the mean and the variance of the LEC increase with the RO design. In fact, the increase of robustness of the UL has a strong impact on the LEC for which mean and variance increase (in RO1 and RO2). Indeed, to increase the robustness of the UL, the sizes of the components (all of them for RO1 and only the PV installation and the battery bank for RO2) have to be increased. The first consequence is that the LEC increases – which can be seen with the increase of its mean -, and the second one is that its variance increases, because every variation on the components economic parameters has a stronger impact.

However, when the objective is not to reach the complete autonomy, i.e. in cases 01, 05 and 1, the RO permits to propose designs which successfully reduce the UL (mean and variance) while keeping similar LEC.

RESPECTIVE CONTRIBUTION OF THE TWO METHODS

As the illustration on this study case shows, the two approaches are from different nature, though they are both based on an uncertainty quantification, which cannot be avoided and include the modeling of the system.

The first proposed approach (NRO/ Uncertainty propagation/ Global sensitivity analysis) differs fundamentally from the RO (i.e. from the second proposed approach) because it has no feedback on the optimization process. The first approach brings information on the following points of interest: (i) what is the impact of the uncertain parameters on the performance indicator of one system? (ii) which of these uncertain parameters are the most relevant to be better known in order to reduce this impact?

The RO on the contrary, has a practical feedback on the optimization process. This second approach duly notes that the level of knowledge cannot be improved and permits to modify the kind of impact of the uncertainty on the optimization results.

The two approaches have complexities and limitations. The first approach, bringing a better knowledge on the uncertainty impact and permitting to identify the important attention points has no practical impact on the system optimization results. The most natural development of this method is then to try to improve the uncertainty quantification. This improvement is not always possible, in particular when dealing with non-fully mature components, as it is often the case in complex energy systems.

The main limitation of the second approach is that it requires significant computational resources and/or time. In fact, the robust optimizations needed respectively 618,700 model evaluations for RO1 and 739,100 for RO2. This high number of required model evaluations is due to, on the one hand, two settled values: the population size of the genetic algorithm and the sampling size of the MC simulation and on the other hand 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 a robust optimization than for a non-robust one. Therefore, we join one of the conclusion of [16] stating that when the computational resources or time is limited, other approaches can be better adapted. Another limitation of this second approach is that it can modify the kind of impact of the uncertainty on the optimization results, but it does not reduce them for every case. In fact in Case 0, the RO shifts the uncertainty from selected outputs to others. It means that the user has to accept that other outputs may be degraded. Moreover, to measure the improvements, but also the losses generated by the RO, the uncertainty propagation is required.

CONCLUSION AND PERSPECTIVES

In this work, we tackle the problem of dimensioning a complex energy system modelled with an important number of uncertain parameters. The sources of uncertainty considered here are the economic and technical parameters of the model, which are of epistemic nature.

Two complementary approaches are proposed to solve this problem. Both begin with an uncertainty quantification step, which consists in the attribution of a probabilistic law to each uncertain parameter values. Both also include the modelling of the system, which is considered here available in the software Odyssey.

The first 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 global sensitivity analysis is performed. These two steps are realized through the coupling between Odyssey and Uranie software [1] [11]. This approach brings information on the impact of the uncertainties on the output of the system results and identifies the most influent uncertain parameters in the output dispersion.

The second approach is the robust optimization of the system, which is performed thanks to the combination of a genetic algorithm and MC simulations. This second approach permits to modify the design of the system itself and the kind of impact of the uncertainty on the optimization results.

These methodologies were applied to the design optimization of the electrical supply of a stand-alone application located in Nigeria, using PV as the main power source. The global sensitivity analysis teaches us that the most influent uncertain parameter in the UL dispersion is the battery capacity loss and in the LEC dispersion is the PV CAPEX. The performed robust optimizations have the objectives to reduce globally LEC and UL for the first one, and for the second the LEC and the UL globally and the dispersion of UL. The obtained configurations are evaluated through uncertainty propagation and gain in the privileged robustness.

There are several interesting points that still have to be thoroughly investigated. The two main axis we want to investigate now are first the inclusion of the stochastic nature of the renewable resources and then the optimization of operation parameters as a way to counter-balance uncertainties on the design of the system.

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