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On the interaction between the design and operation under uncertainties of a simple distributed energy system

Simple
distributed
energy system

AQ:1

AQ:2

AQ: 3

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Abstract

AQ: 4 **Purpose** – The contribution of this work is toward a better understanding of the interplay between the design and the operation under uncertainties of a simple distributed energy system (DES), by analyzing the sensitivity of the operation strategy over the size of the assets.

AQ: 5

Design/methodology/approach – A two-step framework is developed in this work: first, the equipment sizes are obtained solving an integrated design approach where an operation strategy F^d is embedded in a design loop; then, once the sizes have been fixed, the DES is evaluated with an operation strategy F^o (which can be the same as F^d). The operation strategies F^d and F^o are not necessarily the same, so the objective of the paper is to study the interplay between the design and the operation by varying the optimality level of the operation strategies in both phases.

Findings – The results show that the design of DES cannot be approached without considering its close relationship with the operation strategy. Indeed, the design method needs to be chosen according to the performance of the operation policy finally used in real life: no matter if the operation strategies are the same in both phases but they must lead to a similar level of optimality in terms of operating performance.

Originality/value – The originality of this work is to shed light on the importance of the operation strategy in the design procedure as it seems rarely addressed, to the best of the authors' knowledge, in the literature. Indeed, most of the paper dealing with stochastic design of DES solves single large two-stage problems without discussing the way power flows are finally controlled in real life. The optimal design and operation of DES is rarely addressed conjointly, this study aims at bridging the gap between these two isolated scientific communities.

Keywords Microgrids, Distributed energy system, Integrated optimal design, Energy planning, Energy management, Stochastic programming, Uncertainties, Optimal control, Optimal design, Design optimization methodology, Robust design

Paper type Research paper

1. Introduction

The integrated design and operation under uncertainties of distributed energy systems (DES) remain challenging as the problem complexity rapidly grows with the number of scenarios (i.e. sequence of possible realizations of the uncertain parameters over the horizon) (Mavromatidis *et al.*, 2018a). To address this latter issue, *stochastic programming* techniques are oftentimes implemented in the literature where the design problem is formulated in a two-stage fashion over a reduced set of scenario (Birge and Louveaux, 2011; Micheli *et al.*, 2020; Pazouki and Haghifam, 2016). In this way, the operation (i.e. the way power flows are



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controlled over the horizon) is derived over multiple scenarios and nested in a design loop, as the size of the assets depends on the way the systems are operated over time. However, solving such integrated design problem is difficult and inevitable simplifications are made to tackle long computation times. Among those simplifications, the real-time operation strategy is usually simplified, to end up with a single large stochastic optimization problem where operation decisions are indirectly made by assuming perfect foresight of the uncertain parameters over the horizon for each scenario. However, this simplification in the sizing procedure is a modeling approximation to facilitate the resolution of the design problem but the implementation of such operation policy in real life is impossible. Indeed, realistic operation strategies only have access to past and current information. As a result, the performance of the operation strategy used in real life might be lower than the one used to design the system (in the latter case, the future is assumed to be perfectly known for each scenario). Therefore, how to be sure that the required performances will be met with a realistic operation strategy? Is the perfect foresight hypothesis (attached to the operation in the design method) appropriate for the design of DES? Should the operation strategies used for the design and in real life be the same? How sensitive are the design values to the operation policy? Despite their great importance for real-world applications, these design issues are, to the authors' knowledge, rarely addressed in conjunction with realistic operation strategies.

This paper addresses the aforementioned shortcoming by challenging this stochastic design approximation regarding realistic operation strategies which only have access to past and current information. More generally, the contribution of this work is toward a better understanding of the interplay between the design and the operation by analyzing the sensitivity of the operation strategy performance over the size of the assets. To this end, numerical experiments are run on a simple DES (depicted in Figure 1) where the objective is to determine the size of the solar panels (PV) and the Li-ion battery to supply both energy demands with a given share of solar production, at a minimum cost. A two-step framework is developed in this work:

- (1) First, the equipment sizes are obtained by solving an integrated design approach where an operation strategy Φ^d is embedded in a design loop.
- (2) Then, once the sizes have been fixed, the DES is evaluated with an operation strategy Φ^a (which can be the same as Φ^d).

The operation strategies Φ^d and Φ^a are not necessarily the same, so the objective of the paper is to study the interplay between the design and the operation by varying the optimality level of the operation strategies in both phases (see Figure 2 for a schematic view of the problem).

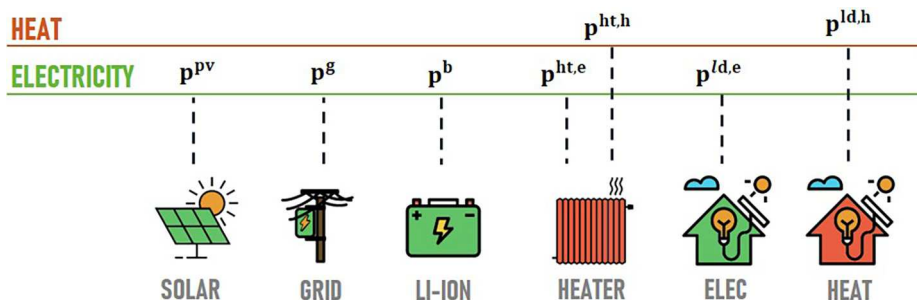
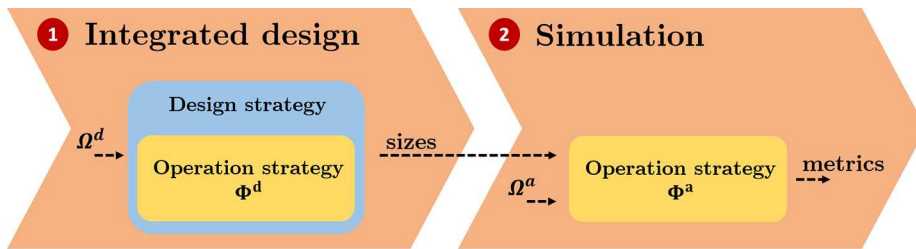


Figure 1. Schematic view of the DES



Simple distributed energy system

Notes: 1) first, the equipment sizes are obtained by solving an integrated design approach where an operation strategy Φ^d is embedded in a design loop. A set of annual hourly energy demands and production scenarios Ω^d is available to solve the optimization problem; 2) then, once the sizes have been fixed, the DES is assessed over a different set of scenarios Ω^a with an operation strategy Φ^a (which can be the same as Φ^d). The operation strategies Φ^d and Φ^a are not necessarily the same, so the objective of the paper is to study the interplay between the design and the operation by varying the optimality level of the operation strategies in both phases

Figure 2. Schematic representation of the two steps framework developed in this work

The paper is organized as follows: first, the mathematical formulation is depicted in Section 2 and the scenario generation method developed in this work is shown in Section 3. Next, the resolution approaches for both the integrated design and the operation are described in Section 4. Finally, results are provided in Section 5, while the discussion and conclusions are drawn in Section 6.

2. Mathematical formulation

In the following, the *deterministic equivalent problem* is formulated over a finite set of scenario Ω as in (Mavromatidis et al., 2018a). The problem is modeled at a hourly time step and operation variables are both indexed by $s \in \Omega$ and $h \in \{1, \dots, H\}$ where H is the horizon of the study (i.e. one year – 8,760 h).

2.1 Decision variables

Decision variables are given as follows:

- The decision variables for the design are the size of the solar panels ($p^{pv,max}$) in kWp and the Li-ion battery capacity ($E^{b,max}$) in kWh gathered in the vector $u^d \in \epsilon^d$. A heater is assumed to be already installed so that its size is not considered as a decision variable in this work.
- The decision variables for the operation are the power flows controlled in the system at each time step and for each scenario. They correspond to the charging ($p_{h,s}^{b,-}$) and discharging ($p_{h,s}^{b,+}$) powers for the battery. The electrical power ($p_{h,s}^{ht,e}$) for the heater and the curtailment power ($p_{h,s}^c$) for solar panels. They are given in kilowatt and gathered in the vector $u_{h,s}^o \in \mathbb{U}_{h,s}^o$.

2.2 Uncertainties

The electrical ($p_{h,s}^{ld,e}$) and thermal ($p_{h,s}^{ld,h}$) demands, the normalized solar production ($p_{h,s}^{pv}$) and the electricity tariff ($c_{h,s}^{g,+}$) are the uncertainties of the problem as their future values cannot

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be predicted with perfect accuracy over the system lifetime. For the sake of simplicity, the electricity feed-in tariff ($c_{h,s}^{g,-}$) is fixed to zero in the rest of the study. They are gathered in the vector $w_{h,s} \in \Omega_{h,s}$.

In this work, a *scenario* is a sequence of realizations over one year at a hourly time step $w_s = (w_{1,s}, \dots, w_{h,s})$ with a given probability π_s .

2.3 Constraints

2.3.1 Energy balances. Both electrical and thermal energy balance constraint must be fulfilled at each time step and for each scenario. they are given by [equations \(1\) and \(2\)](#):

$$p^{pv,max} \cdot p_{h,s}^{pv} + p_{h,s}^{b,+} + p_{h,s}^{g,+} = p_{h,s}^{ld,e} + p_{h,s}^{ht,e} + p_{h,s}^{b,-} + p_{h,s}^c + p_{h,s}^{g,-} \quad (1)$$

$$p_{h,s}^{ht,h} = p_{h,s}^{ld,h} \quad (2)$$

The electrical grid powers $p_{h,s}^{g,+} \leq \bar{g}$ and $p_{h,s}^{g,-} \leq \bar{g}$ are recourse variables for the operation, computed at the end of each time step to mitigate the uncertainties in the system. They are not decision variables of the problem. These latter quantities are limited by the maximum power allowed by the external network \bar{g} . Note that no recourse variable exists for the thermal demand in our model: a lack of supply would result in a temperature discomfort.

2.3.2 Energy system model. The physical models of the assets remain voluntarily simple as the objective of the study is to focus on the design and control methodologies rather than the physical model complexity. Nonetheless, the model granularity is consistent with most of the planning studies encountered in the literature ([Mavromatidis et al., 2019](#)).

Li-ion battery. A generic storage model is implemented and the state of charge dynamic is given by [equation \(3\)](#):

$$E_{h+1,s}^b = E_{h,s}^b \cdot (1 - \eta^{loss} \cdot \Delta) + \left(\eta^- \cdot p_{h,s}^{b,-} - \frac{p_{h,s}^{b,+}}{\eta^+} \right) \cdot \Delta \quad (3)$$

$$\underline{e} \cdot E^{b,max} \leq E_{h,s}^b \leq \bar{e} \cdot E^{b,max} \quad (4)$$

where $E_{h,s}^b$ is the state of charge expressed in kWh, η^- and η^+ are, respectively, the charging and discharging efficiencies, η^{loss} is the self-discharge coefficient and Δ the operation time step (in hours). The state of charge is bounded by a percentage of the maximum storage capacity $E^{b,max}$ (4). The charging and discharging powers are limited by [equations \(5\) and \(6\)](#) as the maximum amount of energy that could be exchanged during a time step is limited:

$$0 \leq p_{h,s}^{b,-} \leq \underline{p} \cdot E^{b,max} \quad (5)$$

$$0 \leq p_{h,s}^{b,+} \leq \bar{p} \cdot E^{b,max} \quad (6)$$

Heater. It converts electricity into heat through a given efficiency $\eta^{e \rightarrow h}$. The conversion equation is given by (7). The heater electrical power is positive and limited by the size of the asset (8).

Simple distributed energy system

$$\dot{p}_{h,s}^{ht,h} = \eta^{e \rightarrow h} \cdot \dot{p}_{h,s}^{ht,e} \quad (7)$$

$$0 \leq \dot{p}_{h,s}^{ht,e} \leq \dot{p}^{ht,max} \quad (8)$$

2.3.3 Share of solar production. The share of solar production $\tau^{share} \in [0,1]$ represents the proportion of the total consumption supplied by the local solar production: a ratio equal to 1 means that all the electricity is provided on-site. Its value is computed based on the amount of energy imported from the utility grid along with the baseline total consumption which includes the electrical and thermal demands through the heater efficiency (9).

$$\sum_s \pi_s \cdot \sum_{h=1}^H \left[\dot{p}_{h,s}^{g,+} - (1 - \tau^{share}) \cdot \left(\dot{p}_{h,s}^{ld,e} + \frac{\dot{p}_{h,s}^{ld,h}}{\eta^{e \rightarrow h}} \right) \right] \cdot \Delta \leq 0 \quad (9)$$

where π_s is the probability of scenario s as the share of solar production is considered as a “soft” constraint in the following work. It only means that it has to be fulfilled according to the expectation risk measure.

2.4 Optimization problem statement

The integrated design objective is to determine the sizing and operation decisions to minimize the sum of both the annualized investment and operating expenditures as it is commonly done in the literature (Gabrielli *et al.*, 2018; Mavromatidis *et al.*, 2018a).

2.4.1 Annualized investment cost. It depends on the size of the equipment and capital cost for both solar panels (c^{pv} in €/kWp) and the Li-ion battery (c^b in €/kWh) (10):

$$J^d(u^d) = \gamma^b \cdot c^b \cdot E^{b,max} + \gamma^{pv} \cdot c^{pv} \cdot \dot{p}^{pv,max} \quad (10)$$

where γ is the annuity factor computed based on the expected lifetime of each equipment with an interest rate of 4.5%.

2.4.2 Operating cost. It depends on the energy exchanged with the utility grid at each time step and for each scenario (11):

$$J_{h,s}^o(u^d, u_{h,s}^o, w_{h,s}) = (c_{h,s}^{g,+} \cdot \dot{p}_{h,s}^{g,+} - c_{h,s}^{g,-} \cdot \dot{p}_{h,s}^{g,-}) \cdot \Delta \quad (11)$$

where $c_{h,s}^{g,+}$ is the tariff of electricity (€/kWh) and $c_{h,s}^{g,-}$ the feed-in tariff (€/kWh), set to zero in the following work.

2.4.3 Problem statement. As previously said in the Introduction, the integrated design problem is a nested optimization problem where the optimal operation problem is integrated in the design loop (12):

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$$\min_{u^d} J^d(u^d) + \sum_s \pi_s \cdot \tilde{J}_s^o(u^d, w_s) \tag{12}$$

where U^d is the set of admissible solution for the design decisions and π_s is the probability to account for the expectation risk measure. The optimal operation problem \tilde{J}_s^o for each scenario s is then given by (13):

$$\begin{aligned} \tilde{J}_s^o(u^d, w_s) &= \min_{u^o} \sum_{h=1}^H J_{h,s}^o(u^d, u_{h,s}^o, w_{h,s}) \\ \text{s.t. } x_{h+1,s} &= f(x_{h,s}, u^d, u_{h,s}^o, w_{h,s}) \\ u_{h,s}^o &\in U_{h,s}^o(u^d, x_{h,s}, w_{h,s}) \end{aligned} \tag{13}$$

where f is defined by the battery state-of-charge equation (3). $U_{h,s}^o$ is the set of admissible solution for the operation which is related to the technical constraints and energy balances defined in section 2.

The operation strategy $\phi_{h,s}: \mathbb{X}_{h,s} \times \mathbb{W}_{h,s} \rightarrow U_{h,s}^o$ gives at each time step the operation decisions $u_{h,s}^o$ as a function of the current state and available information. Several operation policies with different levels of optimality are further introduced in Section 4.

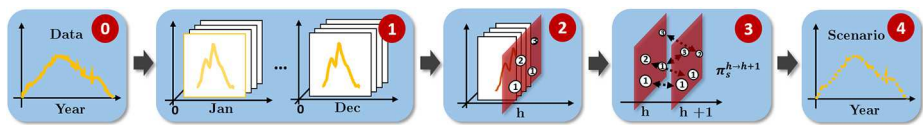
3. Scenario generation

The DES is designed for a five houses district where the supplied energy demand is the aggregation of all house consumptions. The first required step in every stochastic problem is to build a method to generate a large number of plausible scenarios for the uncertain parameters. These scenarios will be used to solve the design optimization problem (12).

The approach implemented in this paper is based on a Markov model as in Patidar et al. (2016), over historical measured residential energy demands and production time series, made freely available by the Australian distributor of electricity (Ausgrid, 2020). To match the paper limitation size, the method is not fully detailed in this paper but readers can refer to Figure 3 and the references for more information about the generation approach.

Concerning the tariff of electricity, a simple statistical model is built upon historical observations of the “flat rate” price of electricity in France over the past 10 years (Eurostat, 2021), by following the methodology developed in (Mavromatidis et al., 2018b). Then, 1,000

F3



Notes: (0) from historical data; (1) days are classified into representatives week and week-end days for each month; (2) for each hour, a given number of states is selected using the k-medoids algorithm. States are aggregated (to keep the synchronicity) and normalized vectors of energy demands (i.e., electrical and thermal consumption) and production; (3) then the transition matrices based on the probabilities of going from one state to another between two consecutive hours are computed; (4) and finally, synthetic scenarios are generated by giving an initial state, a timestamp and the length of the horizon

Figure 3. Description of the scenario generation method based on Markov chains

F4

annual scenarios at hourly time step of both energy demands, production and electricity tariff are generated and randomly combined to fairly represent the stochastic processes. The final set is split into two distinct parts: odd scenarios (Ω^d) will be used for the design phase and even scenarios (Ω^a) will be used for the assessment phase, to avoid any bias in the evaluation procedure (see Figure 2). Figure 4 shows the annual energy demands variability for both the design and assessment scenario sets.

4. Resolution methods

To study the interplay between the design and the operation, the two-step framework presented in the Introduction, is depicted in Figure 2. Both the operation strategies, with the different levels of optimality, and the integrated design methods are introduced in what follows.

4.1 Operation strategies

4.1.1 Anticipative policy. For each design, the most efficient operation strategy is obtained by finding the exact solution of problem (13), which implies that all the information (i.e. realizations of the uncertain parameters) is available over the entire horizon for each scenario. The implementation of such “anticipative” (as the future is assumed to be perfectly known) policy is, of course, unfeasible in real life as uncertainties unfold progressively over time. However, its computation gives a lower bound to the operating cost which is a valuable information to measure the performance of any other realistic operation strategy.

4.1.2 Rule-based policy. The previous unrealistic operation policy will be compared to heuristic strategies based on a set of rules with decreasing performances. The first rule-based (RB) strategy is defined as follows: first, the heater is used to supply the thermal demand. Then, the solar production is directly consumed to supply both the electrical demand and the heater consumption. Finally, the battery is charged whenever there is surplus of energy or discharged otherwise. Then, four other RB policies are built upon the previous strategy by adding an increasing white noise perturbation to the final battery power flow decision. Therefore, the operation strategies range from the most efficient but

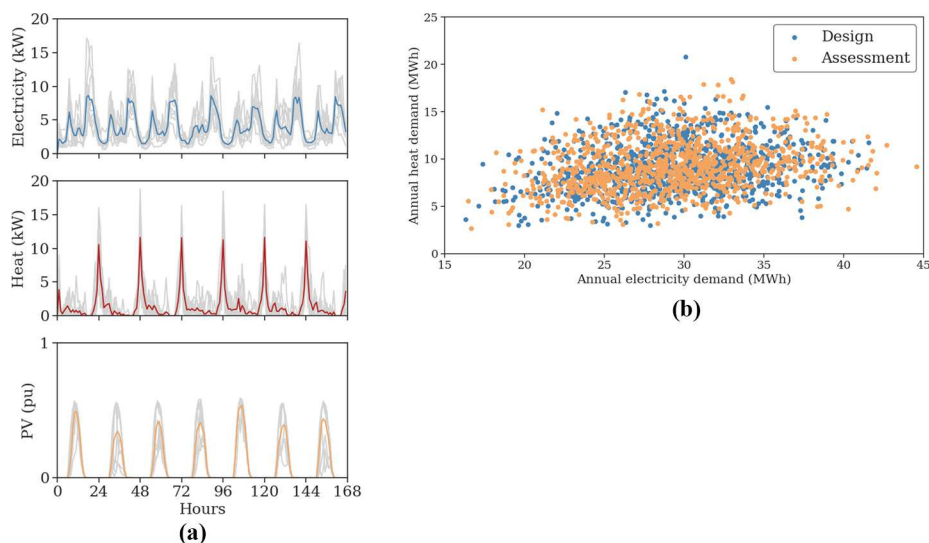


Figure 4.
(a) 10 scenarios of energy demands and production over one week generated using the Markov model (in gray). The colored lines are mean values.
(b) Annual energy demands variability for both the design and assessment sets

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unrealistic anticipative policy to the last RB strategy with poor performances due to the added perturbation. For the sake of simplicity, only the battery power flow decisions are degraded but more sophisticated perturbation could be added to the controller. The only objective is to end up with a range of strategies that perform differently.

4.2 Integrated design methods

4.2.1 *Metaheuristic algorithm with a bi-level architecture.* The first method is widely implemented in the literature (Rigo-Mariani *et al.*, 2020) and based on a metaheuristic algorithm with a bi-level architecture: the DES is simulated over a large set of scenario using one of the operation policy previously introduced, and nested in a design loop. The size of the assets is computed through successive iterations until the objective reach a plateau. A homemade algorithm based on niching methods (Petrovski, 1996) is implemented to solve the problem.

4.2.2 *Single large linear optimization problem.* When the anticipative strategy is embedded in the design procedure, a single large linear optimization (LP) problem is formulated and solved by calling an external solver (for instance, see Cuisinier *et al.*, 2021, for more details). The solver not only computes the optimal sizes but also the optimal power flow decisions at each time step and for each scenario.

4.2.3 *Scenario reduction.* Solving such design problem directly over the 500 scenarios Ω^d would result in intractable computational times. Therefore, a *scenario reduction* method based on clustering is implemented to reduce the sample space as it is commonly done in the literature for stochastic problems (Birge and Louveaux, 2011). The number of optimization scenario is fixed using stability tests. In our case study, 40 scenarios are needed with each probability equal to the number of cluster assignments.

5. Numerical experiments

5.1 Input parameters

Input technical and economic parameters are mainly based on (Petkov and Gabrielli, 2020) and listed below:

- The cost of solar panels is set to 1,300€/kWp with an expected lifetime of 25 years.
- A 30 kW heater is assumed to be already installed to supply the thermal demand.
- The Li-ion battery parameters are given in Table 1.

T1

The problem is modeled using Julia and run on a standard Intel(R) Core(TM) i5-7200U CPU @ 2.5GHz 2.7GHz computer. The design problem with the anticipative controller is formulated using the JuMP package and solved with the IBM CPLEX 12.9 solver.

5.2 Sensitivity of the operation strategy performance over the design

The objective of this section is to successively run the design algorithm with each operation strategy previously defined in Section 4.1 and to compare the resulting equipment sizes. Two special cases are further studied in the following: a first case without any share

Table 1. Li-Ion battery input parameters

	η^+ [0–1]	η^- [0–1]	η^{loss} [h ⁻¹]	\bar{e} [0–1]	\underline{e} [0–1]	\bar{p} [h ⁻¹]	\underline{p} [h ⁻¹]	Lifetime [years]	Cost [€/kWh]
Li-ion	0.9	0.9	0.0005	0.8	0.2	1.5	1.5	12	300

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F5

constraint (i.e. $\tau^{share} = 0$) where the benefit from installing solar panels and storage systems is purely economic; and a second case with a strong renewable share (arbitrarily set to 80%).

Figure 5 shows the sizing as a function of the operation policies. Without any share constraint, the size of the battery decreases to zero along with the performance of the operation policy as it makes no sense to install a battery if it is misused. The LP and RB1 policies give approximately the same design results. On the other hand, when 80% of solar production (in expectation) is required, the optimizer has to oversize the assets to compensate poor energy management performances: the difference goes up to +70% for solar panels and +40% for the battery between the best and the worst strategy. However, in this second case, design values are less sensitive to the operation policy as the results are nearly the same for the first three strategies.

Therefore, the operation policy embedded in the design phase (i.e. Φ^d in Figure 1) and the one used in real-life (i.e. Φ^r) do not have to be the same, but their levels of optimality must be similar. In practice, it only means that the mathematical programming method can be used instead of the metaheuristic procedure, only if the system is finally operated in real life with the RB1 or RB2 policies (depending on the renewable share constraint).

5.3 Sensitivity of the operation strategy over the out-of-sample cost

F6

Once the system has been designed, the objective of this section is to assess each sizing solution with the different operation strategies. The assessment results over the 500 scenarios Ω^a are given in Figure 6. For each table, a row is associated to one design obtained with the corresponding operation strategy. Then, each design is evaluated with all the operation strategies (one for each column) and the resulting total annual cost expected value is printed in the table. When the renewable share expected value is not met, the cell is left blank [Figure 6(b)].

Without any constraint, the worst total annual costs (about +10% compared to the lowest cost) are obtained when the DES is designed with high-performance policies (LP or

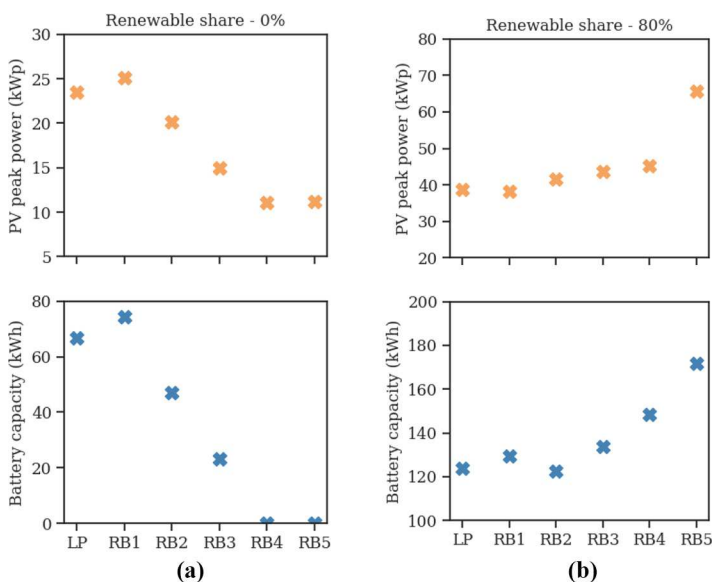


Figure 5. Design results for both assets as a function of the operation policy (a) without the share constraint; (b) with a renewable share equal to 80%

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RB1) and then operated with the low performance RB5 policy (upper right corner). Note that the cost remains constant when the DES is designed with both RB4 and RB5 (whatever the assessment strategy) as the size of the battery is null [see Figure 5(a)]. Concerning the constrained case, the renewable share might not be met if the operation strategy used to design the DES performs better than the one used for the assessment [blank cells in Figure 6(b)]. In every case, the total annual cost is lower when the system is finally operated with a more effective policy than the one used in the design phase (lower matrix triangle). Therefore, an important remark from these observations is that it is safer to use a poor energy management strategy to design the system and then use an operation strategy that performs well in real-time, than the opposite. Otherwise, techno-economic requirements might not be met, with a higher total annual cost than expected.

6. Discussion and conclusions

The interaction between the design and the operation under uncertainty was studied in this work. First, the mathematical formulation was described, where the integrated design problem includes both the investment and operating cost. Then, the two-step framework along with the different design and operation strategies (with decreasing levels of optimality) were introduced. The results show that the design of DES cannot be approached without considering its close relationship with the operation strategy. Indeed, the design method needs to be chosen according to the performance of the operation policy finally used in real life: no matter if the operation strategies are the same in both phases but they must lead to a similar level of optimality in terms of operating performance.

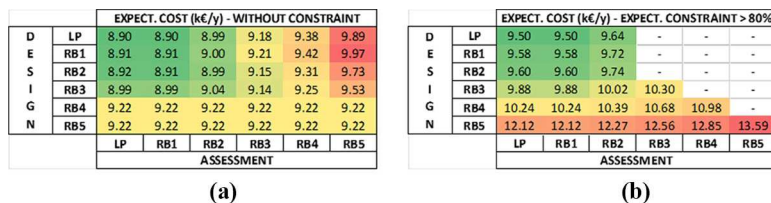
The modeling framework introduced in this work (i.e. the optimization and assessment phases are clearly divided into two parts) provides a way to ensure that the performance are met in real life using realistic operation strategies regardless the approximations made in the design phase. Indeed, design optimization models are usually simplified to come up with a solution in a reasonable time, but the resulting sizing values must be evaluated in a realistic manner to guarantee that the requirements will be met in the real life.

Finally, quantitative results of this work are obviously case study dependent and their values might be strongly criticized. However, this work provided a modeling framework to rigorously study such issue and a way to visualize the results through design/operation interaction matrices. This study could be considered as a first step to anyone interested in thorough investigations over this topic which might be highly relevant in the future as the operation of DES tends to be more and more sophisticated.

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Figure 6.

Expected total annual cost for each design value evaluated with each operation policy (a) without the share constraint; (b) with a renewable share equal to 80%. When the renewable share expected value is not met, the cell is left blank



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