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Highlights

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Dynamic aware aging design of a simple distributed energy system: a comparative approach with single stage design strategies.

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ABSTRACT

This paper focuses on the integrated management and design of a distributed energy systems (DES) with solar generation and energy storage. The DES remains voluntary simple as the objective is to focus on the design methodologies rather than the system complexity. The article aims at bridging the gap between conventional DES design strategies, made in a single stage fashion over a representative period, and expansion planning problems that perform dynamic sizing over decades with oversimplifications of the system operations. Especially, the paper investigates to what extent the value of the model is increased when aging is controlled over the system lifetime compared to standard methods based on a single equivalent year. To address these questions, a multi-time scale model is first implemented by coupling both the DES operation and the sizing. The optimal asset capacities are computed in the form of a dynamic investment plan over the system lifetime that can accommodate potential changes in energy prices or cost of technology. Then, the results are compared with single stage design strategies on a common simulation framework. The implemented multi-time scale planning displays good performances with up to 20% cost reduction compared to typical single stage designs. Finally, the impact of the energy rates and system self-sufficiency are investigated. The obtained results show that significant investments in energy storage arise for electricity prices multiplied by three compared to the baseline or with strong self-sufficiency constraint over 60%.

1. Introduction

The integration of renewable energy sources into conventional systems has been extensively addressed in the past two decades with the need for reduced carbon emissions and in order to tackle the limitation of fossil fuels. In particular, the concept of Distributed Energy System (DES) has emerged and highlights the resources connected closer to the end-user and the implementation of local energy management strategies with both generation and consumption on site. The integrated management and design of DES have then been widely investigated and is oftentimes expressed in the form of optimization problems which minimize a trade-off between the operating costs and the capital expenditures [1]. Different optimization architectures are considered in the literature with (i) “all in one” approaches where sizing and operating parameters are variables of a single optimization problem [2, 3] and (ii) bi-level optimizations with an inner loop that simulates the system operation and an outer loop (usually metaheuristics) that investigates different system configurations (i.e. type and size of assets) [4, 5].

The main challenge of such problems is to tackle the mathematical complexity and the necessity to avoid prohibitive computational times, especially due to the need to simulate the system operation over long time horizons before finding the optimal configuration. In order to ensure tractability, the problems are usually simplified by means of linearization techniques or mixed integer linear programming (MILP) as in [2, 3]. Also, the systems are often simulated over reduced periods of time from sets of typical days up to a whole year at the maximum with hourly or half hourly time steps [6, 7, 8, 9], in order to represent the daily, weekly and seasonal variations for the loads and renewable based generation. The equivalent annualized cost (EAC) becomes the criteria to minimize and is assumed to be constant over the system lifespan (typically decades). Thus, most of the reviewed DES studies fail to capture the longer term variabilities that may impact the energy prices and cost of technologies (e.g. over decades). Most importantly, the DES are oftentimes designed in a single stage fashion at the beginning of the system lifetime and the optimal sizes of the equipment are expressed as a unique vector. In case the DES includes technologies with lifespans shorter than the study

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Sets		
$h \in \mathbb{H} = \{1, \dots, H\}$	Set of hours	
$y \in \mathbb{Y} = \{1, \dots, Y\}$	Set of years	
Operation variables		
$p_{h,y}^{pv,c}$	PV curtailed power in hour h in year y	[kW]
$p_{h,y}^{b,+}, p_{h,y}^{b,-}$	Battery charge/discharge power in hour h in year y	[kW]
$p_{h,y}^{g,+}$	Grid power in hour h in year y	[kW]
$E_{h,y}^b$	Battery state of charge in hour h in year y	[kWh]
$H_{h,y}^b$	Battery state of health in hour h in year y	[kWh]
Investment variables		
r_y^{pv}	New PV size in year y	[kWp]
r_y^b	New battery size in year y	[kWh]
$p_y^{pv,max}$	PV peak power in year y	[kWp]
$E_y^{b,max}$	Battery capacity in year y	[kWh]
Parameters		
τ	Discount rate	[0,1]
η^-, η^+	Battery charge/discharge efficiencies	[0,1]
\underline{e}, \bar{e}	Battery lower/upper SoC bound factors	[0,1]
\underline{p}, \bar{p}	Battery lower/upper power bound factors	[h ⁻¹]
n_c	Battery max. number of cycles	[-]
dod	Battery depth-of-discharge	[0,1]
$p_{h,y}^{ld}$	Load input profile in hour h in year y	[kW]
$p_{h,y}^{pv}$	PV normalized input profile in hour h in year y	[pu]
τ_y^{self}	Self-sufficiency ratio in year y	[0,1]
$\overline{r_y^{pv}}$	Max. PV capacity installed in year y	[kWp]
$\overline{r_y^b}$	Max. battery capacity installed in year y	[kWh]
c_y^{pv}	PV investment cost in year y	[€/kWp]
c_y^b	Battery investment cost in year y	[€/kWh]
$c_y^{g,+}$	Tariff of electricity in year y	[€/kWh]

Table 1
Nomenclature

horizon (e.g. batteries), replacements are taken into account with extrapolation built upon a single simulated year and integrated in the economic analysis *a posteriori*. Typically, the assets are replaced with the same capacities, regardless the potential evolution of input parameters over time such as energy prices, equipment costs and load profiles.

On the other hand, for longer term design, expansion planning studies encountered in the literature correspond to problems where the installation and decommissioning of power plants are investigated over several decades (up to 50 years) at a national scale with the cost of technologies updated over time [10]. However, expansion planning problems often consider oversimplifications of the system operations with limited snapshots or monthly averages which may not be relevant if high shares of intermittent renewable energy production are considered. The authors in [11] and [12] implemented a formulation that integrates multiple time-scales to tackle this latter issue. However, the interaction between investment and operation is not fully captured, i.e. the way systems are operated has no consequences on their aging, thus the number of replacements over the horizon does not depend on the operation (the lifetime of systems are usually fixed *a priori* to their calendar lifetime). This simple trick makes the implementation easier as it is known beforehand when the assets have to be decommissioned, but it is not fully relevant when storage technologies are included in the DES as the number of charge/discharge cycles has great consequences on the equipment lifetime [13, 14].

This paper addresses the aforementioned shortcomings by bridging the gap between the different time scales which is deemed necessary to represent the DES lifetime in the design phase, from hourly variations to years ahead prediction for energy prices and cost of technologies. The main challenge tackled by the paper is to investigate to what extent the value of the model is increased when aging is controlled in the DES design phase compared to standard methods based on a single equivalent year. To address this question, a multi-time scale model is formulated for a simple case

study consisting of a consumer, a solar generator and a battery. The DES remains voluntary simple as the objective is to focus on the methodology and the novelties given by this approach rather than the system complexity. Applying the proposed methodology to more complex DES is definitely the intended direction of future works. The optimal sizing of the system is not expressed as a single vector any longer but as a dynamic investment plan. The article also proposes a reproducible methodology in order to assess the performances of the implemented strategy compared to conventional single stage optimizations. This is allowed by a generic benchmark that simulates the system operation along its lifetime, once the design plan is defined. This common simulator referential, may or may not embed the same profiles and parameters as the ones considered in the design phase. The objective is to provide a common framework in order to equally discriminate different planning strategies which is not commonly encountered in the literature. To summarize, the main contributions of this work are:

- Implementation of a multi-time scale model where the interaction between investment and operation is taken into account for the design of energy systems.
- Introduction of a generic framework (common simulator referential) to compare and to assess the performances of the different design strategies.
- Comparison of the aging aware approach with more standard methods based on single equivalent years, in terms of cost and computational performances.
- Sensitivity analysis with regard to different energy prices and constraint for the system self-sufficiency (i.e. minimum import of energy from the upstream grid).

The paper is organized as follows: section 2 shows the problem formulation of the multi-time scale model and the optimization problem statement. Then, section 3 describes the resolution methods which are going to be compared. Next, the assessment strategy is introduced in section 4. Finally, results are shown in section 5, conclusions and perspectives are drawn in section 6.

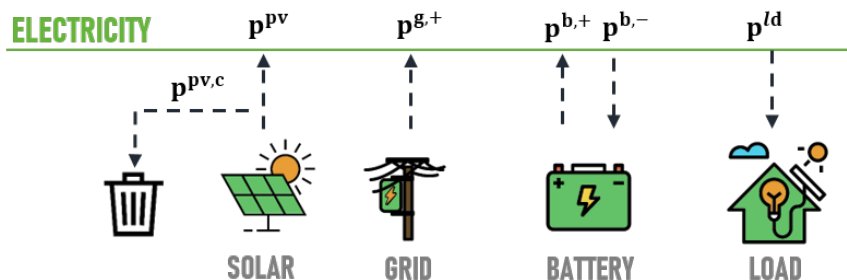


Figure 1: Schematic view of the DES with solar panels and a battery.

2. Mathematical formulation

This section describes the fundamental mathematical equations that allow modeling the DES operation and the impact of investment choices. The presented problem formulation will be considered as the common simulator referential when different design strategies are further discriminated. Note that the design problem will embed similar equations and time series profiles. This strong assumption would be equivalent to a long term deterministic design with “perfect foresight” and no modeling errors. The authors remind that the objective here is to provide a common framework in order to appropriately discriminate different design strategies. Considering the uncertainties for the energy prices, equipment cost or load profiles right from the design phase is not in the scope of this paper. The formulation is then based on [15] applied to the design and operation of the DES. Both the investment and operation dynamics are included into a common optimization problem as described in the following. Note that the main difference with [15] is the comparison of the aware-aging model with other design strategies depicted in section 3. To this end, the current paper is first limited to the deterministic case. This latter hypothesis is further discussed in section 6.

2.1. Notations

The investment dynamic is a slow process compared to the operation where power flow decisions need to be made every hour. Hence, we define two time scales with the set of years $y \in \mathbb{Y} = \{1, \dots, Y\}$ and hours $h \in \mathbb{H} = \{1, \dots, H\}$ with Δ_y and Δ_h the two time steps respectively. A time continuum is ensured as depicted in figure 2. Investment decisions are made along the set \mathbb{Y} (orange nodes) while the operations along both sets \mathbb{Y} and \mathbb{H} (blue nodes).

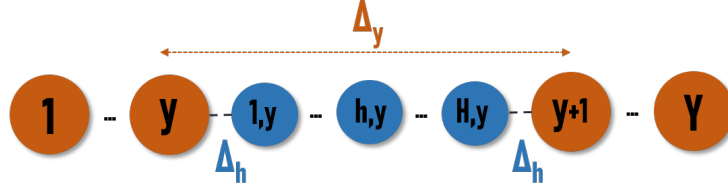


Figure 2: A time continuum is ensured in the simulation between the investment (y) and operating (h) time scale

2.2. Operation time-scale

At the operation time-scale, the decision variables are the charged/discharged power in the battery $p_{h,y}^{b,-}, p_{h,y}^{b,+}$ and the curtailed solar power $p_{h,y}^{pv,c}$. Their limits are represented by constraints (1), (2) and (3). \bar{p} and \underline{p} are the maximum discharging/charging c-rate respectively, which limit the power exchanged by the battery. The grid power $p_{h,y}^{g,+}$ is introduced to make the optimization implementation clearer. This flow is represented as a mathematical variable but does not correspond to any physical degree of freedom for the problem. This latter quantity is also limited (4) by the maximum power allowed by the external network.

$$0 \leq p_{h,y}^{pv,c} \leq p_y^{pv,max} \cdot p_{h,y}^{pv} \quad (1)$$

$$0 \leq p_{h,y}^{b,+} \leq \bar{p} \cdot E_y^{b,max} \quad (2)$$

$$0 \leq p_{h,y}^{b,-} \leq \underline{p} \cdot E_y^{b,max} \quad (3)$$

$$0 \leq p_{h,y}^{g,+} \leq \bar{g} \quad (4)$$

State variables are the battery state of charge (SoC) and state of health (SoH), both of them expressed in kWh here (i.e. available kWh for the SoC and remaining usable kWh for the SoH). The SoC dynamic is given by equation (5) where η^- and η^+ are respectively, the charging and discharging efficiencies. In order to limit the battery degradation due to deep charge and discharge, the SoC has to remain between upper and lower bounds (usually set to 80% and 20% of the battery capacity, respectively) as it is commonly done for Li-ion batteries (6).

$$E_{h+1,y}^b = E_{h,y}^b + \left(\eta^- \cdot p_{h,y}^{b,-} - \frac{p_{h,y}^{b,+}}{\eta^+} \right) \cdot \Delta_h \quad (5)$$

$$\underline{e} \cdot E_y^{b,max} \leq E_{h,y}^b \leq \bar{e} \cdot E_y^{b,max} \quad (6)$$

The battery SoH is computed using a simple model (7) based on the maximum exchangeable energy during its lifespan [13]. This model only considers aging due to cycling. Calendar aging mostly depends on the ambient temperature conditions [16], thus we assume that the temperature is controlled in order to neglect this latter contribution. Furthermore, battery parameters such as loss of capacity or increased internal resistance over time are not taken into account. As in [13], the maximum exchangeable energy depends on the battery maximum number of cycles n_c for a fixed depth-of-discharge dod . The battery is replaced whenever the SoH reaches zero. Thus, its value has to remain positive all along the simulated horizon (8).

$$H_{h+1,y}^b = H_{h,y}^b - (p_{h,y}^{b,+} + p_{h,y}^{b,-}) \cdot \Delta_h \quad (7)$$

$$0 \leq H_{h,y}^b \leq 2 \cdot n_c \cdot dod \cdot E_y^{b,max} \quad (8)$$

Then, the power balance is ensured by (9) where $p_{h,y}^{ld}$ is the power demand and $p_{h,y}^{pv}$ is the PV normalized input profile multiplied by the PV peak power $p_y^{pv,max}$.

$$p_{h,y}^{g,+} + p_y^{pv,max} \cdot p_{h,y}^{pv} - p_{h,y}^{pv,c} + p_{h,y}^{b,+} - p_{h,y}^{b,-} = p_{h,y}^{ld} \quad (9)$$

Finally, a constraint on the self-sufficiency $\tau_y^{self} \in [0, 1]$ is given by (10). The self-sufficiency represents the degree of autonomy for the considered system. It is usually estimated as the share of local consumption supplied by the local generation and can be computed while considering the amount of energy imported from the upstream grid: a ratio equal to 1 means that all the electricity consumed is provided by the installed solar panels [17].

$$\sum_{h=1}^H (p_{h,y}^{g,+} \cdot \Delta_h) \leq (1 - \tau_y^{self}) \cdot \sum_{h=1}^H (p_{h,y}^{ld} \cdot \Delta_h) \quad (10)$$

2.3. Investment time-scale

At the investment time scale, the decision variables are the new capacity installed for the battery r_y^b and the new peak power r_y^{pv} for solar panels that could be made every year. They are both continuous, positive and bounded variables (11), (12).

$$0 \leq r_y^{pv} \leq \overline{r^{pv}} \quad (11)$$

$$0 \leq r_y^b \leq \overline{r^b} \quad (12)$$

In order to properly model the replacement dynamic, a difference is made between the new design of systems and the existing system sizes which have to be updated when investment decisions are made. Thus, unlike single stage investment optimization, state variables are also introduced for the investment. Technology sizes could be increased or downscaled depending on the case study. Note that systems are assumed to be completely replaced when an investment decision is made. Hence, system sizes $E_y^{b,max}$ and $p_y^{pv,max}$ need to be updated with the new installed capacities. Otherwise, they remain the same as the year before. This investment dynamic is given by (13) and (14). Because solar panels aging is not considered in the current study, a linear formulation would have been possible for the investment dynamic of the PV. As it has little consequences on computational times, this generic formulation was adopted in the paper.

$$p_{y+1}^{pv,max} = \begin{cases} r_y^{pv} & , \text{if } r_y^{pv} > 0 \\ p_y^{pv,max} & , \text{otherwise} \end{cases} \quad (13)$$

$$E_{y+1}^{b,max} = \begin{cases} r_y^b & , \text{if } r_y^b > 0 \\ E_y^{b,max} & , \text{otherwise} \end{cases} \quad (14)$$

2.4. Bridging the gap between time-scales

Both operation and investment decisions have to be made over the two time scales horizon. In order to ensure the inter-year continuity for the battery SoC and the SoH, the decision process is defined as follows: investment decisions are made at the end of the last hour of each year (H, y) when the SoH and SoC are completely known over the year.

$$E_{1,y+1}^b = \begin{cases} \bar{e} \cdot r_y^b & , \text{if } r_y^b > 0 \\ E_{H+1,y}^b & , \text{otherwise} \end{cases} \quad (15)$$

$$H_{1,y+1}^b = \begin{cases} 2 \cdot n_c \cdot dod \cdot r_y^b & , \text{if } r_y^b > 0 \\ H_{H+1,y}^b & , \text{otherwise} \end{cases} \quad (16)$$

The capacities of the assets are then updated with the new sizes at the beginning of the first hour of the next year ($1, y + 1$). Furthermore, any newly installed battery is assumed to be fully charged and with a maximum exchangeable energy (i.e. maximum SoH). Thus, continuity equations for the SoH and SoC between years are given by (15) and (16).

Finally $u_y = (p_{1:H,y}^{b,-}, p_{1:H,y}^{b,+}, p_{1:H,y}^{pv,c}, r_y^b, r_y^{pv})$ denotes the decisions variables, and $x_y = (E_{1:H,y}^b, H_{1:H,y}^b, E_y^{b,max}, p_y^{pv,max})$ represents the state variables of the problem.

2.5. Total cost over the horizon

The total cost is the discounted sum of both the investment and operating expenditures over the horizon (17). A salvage value is also introduced to account for the remaining life of the battery at the end of the horizon. Its value is computed according to [18] which assumes a linear depreciation of components over time.

$$L(u, x) = \sum_{y=1}^Y \gamma_y \left(\underbrace{c_y^{pv} \cdot r_y^{pv} + c_y^b \cdot r_y^b}_{\text{Investment cost}} + \underbrace{\sum_{h=1}^H c_{h,y}^{g,+} \cdot p_{h,y}^{g,+} \cdot \Delta_h}_{\text{Operating cost}} \right) - \underbrace{K \cdot H_Y^b}_{\text{Salvage value}} \quad (17)$$

where c_y^{pv} and c_y^b are the investment cost of solar panels (€/kWc) and the battery (€/kWh) respectively. The peak/off-peak tariff of electricity (€/kWh) purchased from the external network is given by $c^{g,+}$ as we assume that no electricity could be sold to the grid. Note that those rates could change over the horizon as they are also indexed by y which motivates the proposed multi-time scale approach. However, evolving energy prices are not introduced here and will be the scope of further studies. The value of the discount factor γ_y is given by (18).

$$\gamma_y = \frac{1}{(1 + \tau)^y} \quad (18)$$

where τ is the discount rate. The salvage coefficient K is the ratio of the discounted investment cost over the maximum exchangeable energy at the end of the horizon (19).

$$K = \frac{\gamma_Y \cdot c_Y^b \cdot E_Y^{b,max}}{2 \cdot n_c \cdot dod \cdot E_Y^{b,max}} = \frac{\gamma_Y \cdot c_Y^b}{2 \cdot n_c \cdot dod} \quad (19)$$

2.6. Optimization problem statement

The formulated problems aim at finding the optimal decision variables for both the operation and the investment in order to minimize the total cost of the system over the horizon (20).

$$\min_{u_1:y} \sum_{y=1}^Y \gamma_y \left(c_y^{pv} \cdot r_y^{pv} + c_y^b \cdot r_y^b + \sum_{h=1}^H c_{h,y}^{g,+} \cdot p_{h,y}^{g,+} \cdot \Delta_h \right) - K \cdot H_Y^b \quad (20)$$

$$x_{y+1} = f(x_y, u_y) \quad (21)$$

$$u_y \in U(x_y) \quad (22)$$

where f is described by equations (5), (7), (13), (14), (15) and (16), giving the dynamic of the system. U is the feasible set defined by the constraints introduced in section 2.

3. Resolution methods

At this point, the integrated design and control problem for the DES is formulated as an optimization problem, the resolution strategies which are going to be compared in section 5 are introduced in this section.

3.1. Method 1: design based on the equivalent annual cost

In the literature, the design of distributed energy systems is traditionally based on a single equivalent year to tackle potential long computation times for complex energy systems [7, 8, 9, 2, 3, 19, 20]. In that case, the component aging dynamic is not anymore considered into optimization. The first method introduced in this paper is then derived from this approach and provides a heuristic policy for the current optimization problem.

In what follows, $u_1^i = (r_1^b \quad r_1^{pv})$ denotes the first year investment decision variables and $u_{h,y}^o = (p_{h,y}^{b,-} \quad p_{h,y}^{b,+} \quad p_{h,y}^{pv,c})$ are the decisions variables for the operation. Note that the set of years y is kept for the operation in order to take the 20 years demand and production profiles into account while the operating cost is ultimately averaged on a single year.

The design is computed the first year by solving a standard equivalent annual cost problem. Then, when the battery reaches its lifetime during the simulation phase, it is replaced with the same capacity as the one initially computed at

the first year (single stage optimization). The resulting design policy is then given by (23) which depends on the state of the system at each investment time step.

$$\phi(x_y) = \begin{cases} u_1^{i,*}, u_{1:H,1:Y}^{o,*} = \arg \min_{u_1^i, u_{1:H,1:Y}^o} \underbrace{\Gamma^{pv} \cdot c_1^{pv} \cdot r_1^{pv} + \Gamma^b \cdot c_1^b \cdot r_1^b + \frac{1}{Y} \sum_{y=1}^Y \sum_{h=1}^H c_{h,y}^{g,+} \cdot p_{h,y}^{g,+} \cdot \Delta_h}_{\text{Equivalent annual cost}} & , \text{ if } y = 1 \\ u_1^{i,*} & , \text{ if } H_{H+1,y}^b = 0 \\ 0 & , \text{ otherwise} \end{cases} \quad (23)$$

where the annuity factor Γ is introduced. This latter quantity is computed based on the interest rate τ and the expected lifetime T (in years) of each system (24) as it is commonly done in [7, 8, 9, 3, 19, 21].

$$\Gamma = \frac{\tau(\tau + 1)^T}{(1 + \tau)^T - 1} \quad (24)$$

3.2. Method 2: design based on the equivalent annual cost with online re-optimization

The second method is similar to method 1 except that the optimization is rerun every time the battery reaches its end of life and needs (or not) to be replaced. Instead of replacing the battery with the same capacity computed at the first year, new design decisions can be made with updated information (e.g. equipment cost, energy prices, etc.). Because the PV lifetime is assumed to be longer than the horizon, its capacity remains fixed to its first year value and no replacement may be needed. The formulation is unchanged from method 1 but the investment costs and the number of remaining years Y before the end of the horizon are updated with current values (i.e. when the storage reaches its end of life). The heuristic policy for the design is given by (25).

$$\phi_y(x_y) = \begin{cases} u_1^{i,*}, u_{1:H,1:Y}^{o,*} = \arg \min_{u_1^i, u_{1:H,1:Y}^o} \Gamma^{pv} \cdot c_y^{pv} \cdot r_1^{pv} + \Gamma^b \cdot c_y^b \cdot r_1^b + \frac{1}{Y} \sum_{y=1}^Y \sum_{h=1}^H c_{h,y}^{g,+} \cdot p_{h,y}^{g,+} \cdot \Delta_h & , \text{ if } H_{H+1,y}^b = 0 \\ 0 & , \text{ otherwise} \end{cases} \quad (25)$$

3.3. Method 3: aware aging design based on the multi-time scale model

The third method solves the entire multi-time scale problem by formulating a single large MILP problem. Big-M values with binary variables are introduced in order to linearize "if-else" functions (14) - (16) as it is commonly done in MILP formulation. As an example, the investment dynamic equation (14) for the battery becomes (26) and (27) and allows ensuring the inter-year continuity as previously mentioned.

$$-M \cdot (1 - \delta_y^b) \leq E_{y+1}^{b,max} - r_y^b \leq M \cdot (1 - \delta_y^b) \quad (26)$$

$$-M \cdot \delta_y^b \leq E_{y+1}^{b,max} - E_y^{b,max} \leq M \cdot \delta_y^b \quad (27)$$

M is the big-M value equal to the sizing bounds and δ_y^b a binary variable which is equal to 1 when $r_y^b > 0$. In that way, if $r_y^b > 0$ then $E_{y+1}^{b,max}$ is equal to r_y^b thanks to (26), otherwise the capacity is unchanged from the previous year (27).

4. Assessment

The main objective of the study is to compare the aware aging design technique with the other strategies based on the equivalent annual cost. In order to get a fair comparison between those approaches, a common simulation referential is built upon the mathematical description of section 2 which includes the aging and replacement dynamic properly modeled. In that way, the performance of each approach could be rigorously measured, despite the simplifications made for the purpose of optimization. The physical equations of the energy systems, the aging and replacement dynamics implemented in the simulator are those described in section 2 for the sake of consistency. In practice, different set of models (e.g. more accurate, non linear, etc.) could also be used but it is not in the scope of this paper.

The main focus here is to have a common ground referential for the methods comparison. The process is described in figure 3. With method 3, because the input parameters (i.e. load profiles, energy prices, equipment costs, etc.) and the modeling are the same in the design phase and in the assessment phase, the results from both cases (design and simulation) are obviously identical.

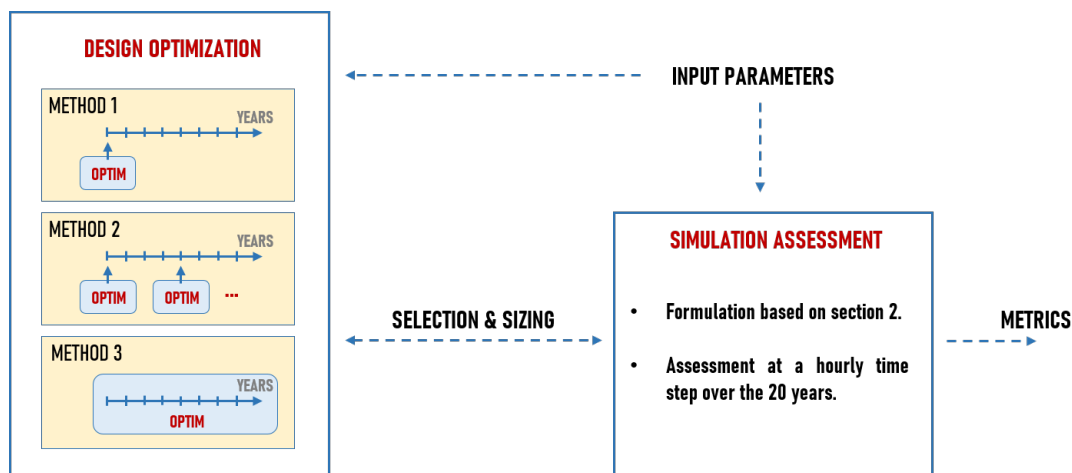


Figure 3: Assessment framework to compare the different methods. With method 3, because the input parameters (i.e. load profiles, energy prices, equipment costs, etc.) and the modeling are the same in the design phase and in the assessment phase, the results from both cases are identical.

Metrics: In addition to the total cost defined by (17), the net present value (NPV) is also computed to assess the performance of each method as an output from the simulation phase. It is a standard metric to compare different investment projects [21, 18] as it gives extra information about the profitability along the system lifetime. This latter quantity is determined by computing the difference between positive cash flows and investment costs. A positive NPV results in profit: the higher the NPV at the end of the horizon, the higher the profitability. In the study, cash flows correspond to savings compared to the baseline cost where all the electricity is purchased from the main upstream grid.

In next section, design values, the NPV and computational times are going to be compared in order to have a fair comparison between those design methods. The best method is the one with the highest NPV while fulfilling the self-sufficiency constraint.

5. Numerical results

The aim of this section is to demonstrate novelties from the multi-time scale approach compared to the other resolution methods. Several examples will be introduced in order to highlight some specific points.

5.1. Case study

Input data and variables are listed below:

- The electrical demand and production profiles come from Ausgrid (australian distribution network) [22] which openly provides measured data at a 30 min time step from 300 residential consumers over 3 years. Among the available profiles, [23] identified a "clean dataset" which gathered 54 consumers around Sydney and Newcastle with similar power range. For each year of the 20-years horizon, 10 consumers profiles were randomly chosen and aggregated as input of the study (the solar profiles were also normalized). The demand and production variability between years is taken into account as each yearly profile is different from the others (see appendix A).
- The tariff of electricity follows a peak/off-peak EDF "Tarif Bleu" [24]. For the sake of simplicity, no price evolution is taken into account over the 20 years.

Parameters	η^-	η^+	\underline{e}	\bar{e}	p	\bar{p}	n_c
	[0-1]	[0-1]	[0-1]	[0-1]	[h ⁻¹]	[h ⁻¹]	[-]
Battery	0.8	0.8	0.2	0.8	1.5	1.5	2500

Table 2
Battery parameters

- The cost of storage system (Li-ion battery + converter) is given by [25] and decreases from 600 €/kWh in 2021 to 300 €/kWh in 2040 (see appendix A).
- The cost of solar panels including AC/DC converters is given by [26] and decreases from 1040 €/kWc in 2021 to 735 €/kWc in 2040 (see appendix A).
- The discount rate τ is set to 4.5%.
- Technical parameters for the battery are reported in table 2.

The problem is modeled using Julia and JuMP package [27]. The IBM CPLEX 12.10 solver is then used to solve the problem. All the computations are run on a Intel Xeon(R) CPU E5-2697 v2 @ 2.70 GHz x 48 server.

5.2. Example 1: comparison with a self-sufficiency constraint set to 60%

With the current low electricity tariffs and costs of technologies, none of the three methods would invest in a Li-ion battery due to high capital expenditure compared to the expected savings on the operation. Thus, in order to compare the results from the different approaches, a first example is introduced where the self-sufficiency ratio is arbitrarily set to 60% in order to justify the installation of a storage system.

Figure 4 shows the planning strategy over the horizon for the three methods with a 60% self-sufficiency ratio. Note that the assets are assumed to be installed at the end of the first year in order to be operated the first hour of the second year. As shown in the figure, method 3 installs 75 kWp of solar panels and 182 kWh of battery the first year. Then, the battery is replaced once the 9th year by a new 205 kWh asset (+23 kWh compared to the initial investment) which occurs when the SoH reaches zero (see figure 5). Figure 5 shows that the multi-time scale formulation handles correctly continuity issues and aging is controlled in order to install the new battery when the previous is out of order.

For the methods 1 and 2, the sizing results are the same in both cases with 88 kWp of PV and 188 kWh of storage installed the first year. Then the battery is replaced two times, the 8th and the 15th year with the same capacity as in the first year. Remind that method 2 reruns the optimization at the end of the battery lifetime whereas method 1 installs the same initial capacity at each replacement. The optimizer in method 2 does not take advantage of the investment cost reduction to increase the battery capacity when it has to be replaced. Indeed, even with cost decrease and current energy prices, it is not economically profitable to purchase battery storage so that the optimizer installs just enough battery and PV to ensure the self-sufficiency constraint fulfillment until the end of the simulated horizon. In both cases, the SoH is not controlled during operation and the battery need to be replaced one more time compared to method 3. However, at the end of the horizon, the storage systems are still "usable" and the remaining SoH (as a percentage of the total exchangeable energy) is 35% for both methods.

As shown in figure 6, the self-sufficiency constraint is fulfilled each year with every method. Concerning method 3, the optimizer operates the DES and installs just enough capacity to fulfill the constraint each year with less margin than the other strategies. In contrast, method 1 and 2 optimize the system to fulfill the constraint during the worst years when the net energy demand is the higher which leads to greater self-sufficiency ratio for the rest of the years as the operation takes advantage of the system oversizing.

Economical results are depicted in table 3. Note that with current economic hypothesis, the DES is not profitable over 20 years due to high installation cost of the battery. The reference cost is then lower than the optimal results obtained with the self-sufficiency constraint and the NPV is here given for information purpose only (negative values for all the methods). As shown in the table, the total discounted cost over the 20 years is 10% lower with method 3 than with the other methods. Note that the results of method 1 and 2 are approximately the same.

Finally, the better performances of method 3 are obtained at the cost of greater computational time with 24h long calculation where method 1 is run in only 5 min and method 2 in 15 min. Even if the number of variables and constraints

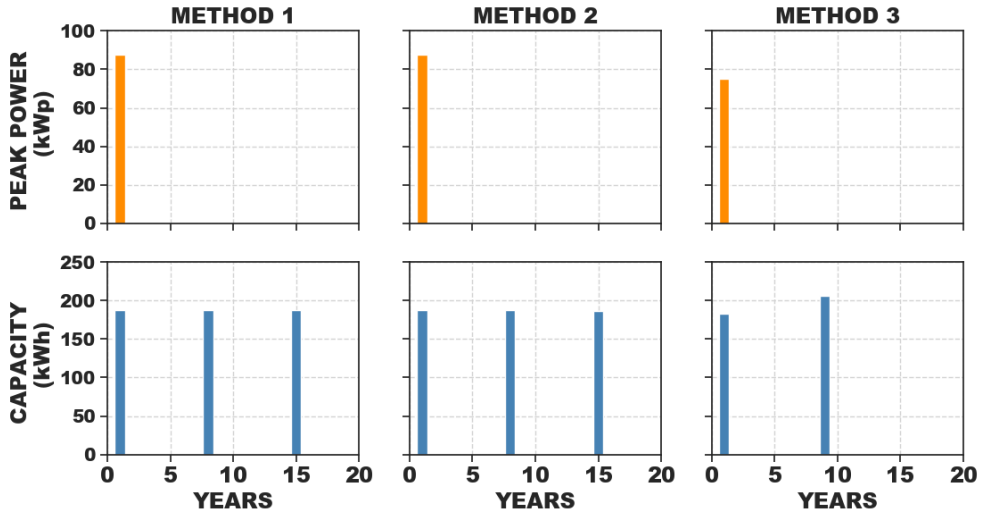


Figure 4: Planning strategy over the horizon with a 60% self-sufficiency ratio.

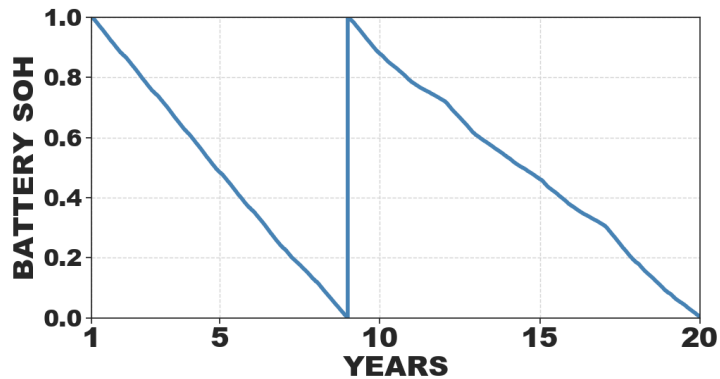


Figure 5: The battery SoH over the horizon with method 3 and a 60% self-sufficiency ratio. The SoH has been normalized by the maximum exchangeable energy in the figure.

are in the same range between the different methods (see table 4), the complexity in the third approach is increased with the introduction of binary variables for the inter-year continuity on the investment decisions.

As a conclusion of this section, the results could be summed up as follows:

- With the multi-time scale approach, aging and number of replacement are controlled over the whole time horizon.
- The sizing could whether be increased or down-scaled each year with method 3.
- It pays to control aging as the total discounted cost over the horizon is 10% lower than with the other strategies on the considered test case.
- The last method suffers from longer computational times compared to the other approaches.

5.3. Example 2: comparison with a higher electricity tariff

The aim of this section is to compare the three methods in a case where it is profitable to install a Li-ion battery without the self-sufficiency constraint. This could be obtained by assuming a lower investment cost of systems or with

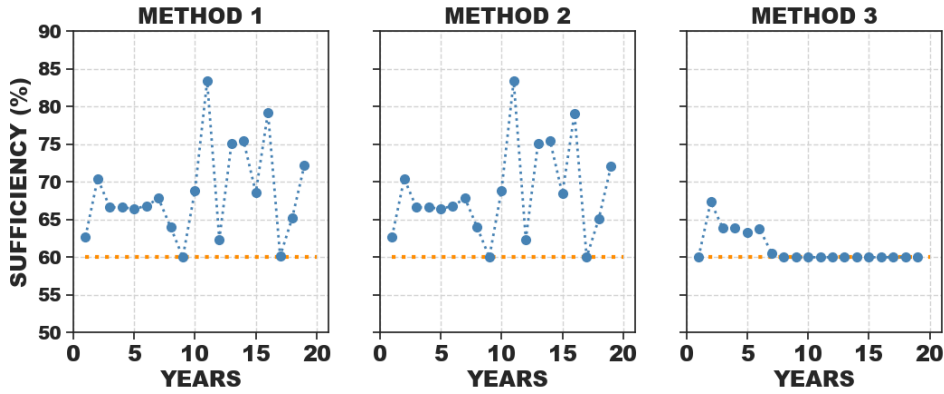


Figure 6: Self-sufficiency constraint for each method after simulation. Its value was set to 60%.

	Ref.	Method 1	Method 2	Method 3
OPEX [k€]	185.8	62.5	62.5	72.4
CAPEX [k€]				
Li-ion	-	205.4	205.2	167.9
PV	-	87.0	87.0	74.8
Salvage [k€]	-	-8.4	-8.3	-
Total [k€]	185.8	346.5	346.4	315.1
NPV [k€]	-	-160.7	-160.7	-129.3
CPU time	-	5 min	3 × 5 min	24 h

Table 3

Comparison of the total discounted costs over the 20 years and CPU time (computational time required to solve the model) between the three methods with a self-sufficiency ratio set to 60%. The reference case where all the electricity is bought from the grid and the NPV are given for information purpose.

	Variables	Constraints
Method 1 & 2	876 022	1 927 304
Method 3	1 051 362 (38 bin)	2 444 637

Table 4

Comparison of the complexity between the three methods.

increased tariff of electricity. The latter strategy is chosen and the tariff of electricity is multiplied by 5 in order to have a battery installed the first year.

As shown in figure 7, every method approximately installs the same battery capacity the first year (260 kWh). Then, both methods 2 and 3 take advantage of lower storage costs to increase the size of the battery. While method 3 only replaces the battery once with a 394 kWh asset (+134 kWh), method 2 replaces the storage twice with greater capacities: 280 kWh (+20kWh) the first time and 311 kWh (+51kWh) the second time. Similar to the test performed in the previous section, the battery is out of order at the end of the horizon for method 3 whereas it remains 50% and 54% of the total exchangeable energy for method 1 and 2 respectively. Concerning the PV, both method 1 and 2 install 116 kWp of solar panels which is 24 kWp greater than method 3. Compared to the previous section, the solar panel size increases when the electricity gets more costly, but no additional investment is made over the horizon. This latter aspect may be explained because when investment decisions are made, technologies are entirely replaced by new systems according to the modeling developed in this work. The cost induced is then proportional to new sizes instead

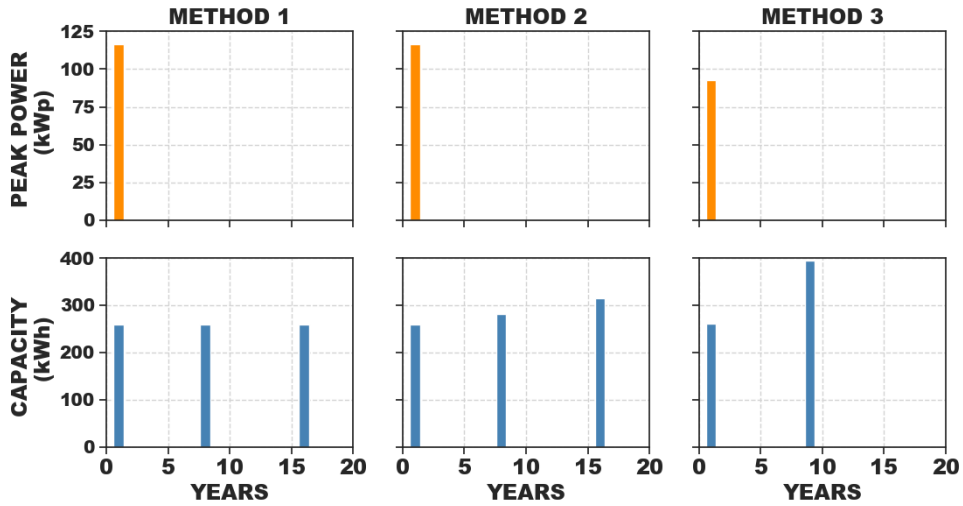


Figure 7: Planning strategy over the horizon with a tariff of electricity multiplied by 5.

	Ref.	Method 1	Method 2	Method 3
OPEX [k€]	929.0	210.5	197.6	213.0
CAPEX [k€]				
Li-ion	-	280.3	296.8	270.8
PV	-	115.8	115.8	91.8
Salvage [k€]	-	-16.6	-21.9	-
Total [k€]	929.0	590.0	588.3	575.6
NPV [k€]	-	339.1	340.8	353.4
CPU time	-	5 min	3 × 5 min	24 h

Table 5

Comparison of the total discounted costs over the 20 years and CPU time between the three methods with the tariff of electricity multiplied by 5.

of additional investment only. Thus, technologies with longer lifespan than the horizon are preferably installed the first year. Similar to previous section, the economic results are given in table 5. As previously mentioned, the DES is profitable in every cases and the NPV at the end of the 20 years corresponds to profits compared to the baseline case without solar panels and battery. The differences between the NPV values are lower than in previous case: the profit is 4% greater with method 3 than method 1 and 3.6% greater than method 2. Note that the resulting NPV of method 1 and 2 are again approximately the same.

An interesting point is highlighted in figure 8. In that case, the tariff of electricity is multiplied by 3. Unlike the other methods, method 3 installs 48 kWp of solar panels the first year but waits until the 11th year to purchase a 134 kWh battery when its cost is divided by 1.5. The multi-time scale approach not only optimizes the size of technologies, but also determines the optimal timing (investment pathway) to install the components along the horizon. This result is only made possible with the use of the proposed method 3 as the design is reconsidered each year in the formulation. This latter aspect gives more flexibility to the approach when strong evolution occurs over the input parameters.

Again, the NPV of method 1 and 2 are approximately the same while it is 20% higher for method 3 in this case.

5.4. Sensitivity analysis of the self-sufficiency ratio and electricity tariff over the design of the DES

The self-sufficiency ratio and electricity tariff consequences for the design of the DES are assessed by varying these latter parameters. The former quantity varies from 0% to 100% (100% when all the electricity consumed is provided by

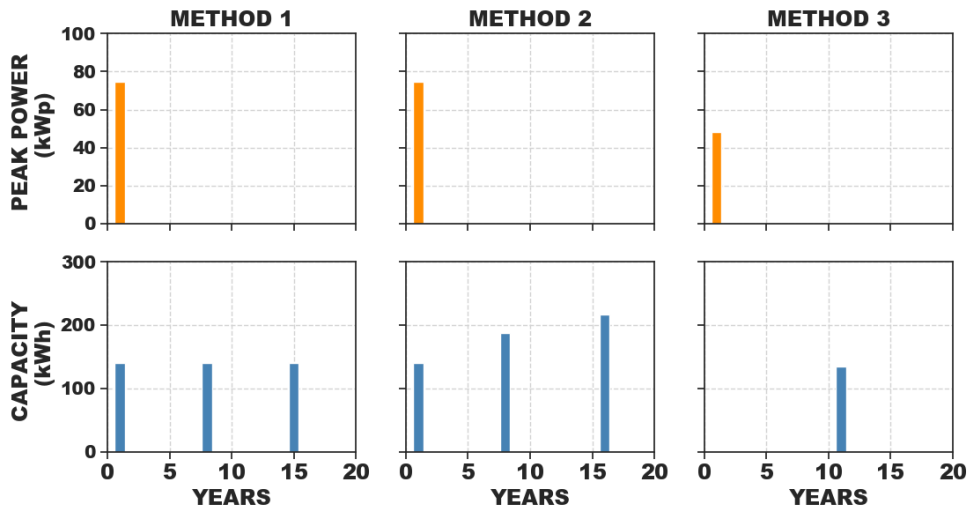


Figure 8: Planning strategy over the horizon with a tariff of electricity multiplied by 3. Unlike the other methods, method 3 waits until the 11th year to install the battery at a lower cost than first year.

	Ref.	Method 1	Method 2	Method 3
OPEX [k€]	557.4	233.7	214.3	345.7
CAPEX [k€]				
Li-ion	-	153.2	179.8	35.3
PV	-	74.2	74.2	48.1
Salvage [k€]	-	-6.2	-14.5	-
Total [k€]	557.4	454.9	453.8	429.1
NPV [k€]	-	102.4	103.5	128.4

Table 6

Comparison of the total discounted costs over the 20 years between the three methods with the tariff of electricity multiplied by 3.

the local generation) and the tariff of electricity is increasingly multiplied from 1 to 3. The multi-time scale approach is run for this section.

Figure 9 depicts the NPV as a function of both parameters. The black line delimits the area (under the line) where the DES is economically profitable over the 20 years (NPV greater or equal to zero). Remind that a NPV equals to zero means that the DES is paid back without any profits. With current electricity tariff and costs of technologies, no more than 30% of self-sufficiency is affordable without losing money over the 20 years. This is achieved with only 35 kWp of PV used in self-consumption without any battery to store the surplus of energy. When the tariff is multiplied by two and three, this value increases to 55% and 83% respectively.

Two specific cases are going to be further studied: 1) the self-sufficiency ratio is increased while the price of electricity remains fixed to its current value (tariff multiplier equals to 1); 2) the self-sufficiency constraint is set to zero and the tariff of electricity is increased up to 3 times the current price. The results are shown in figure 9.

As we can observe in the first case, with 20% of self-sufficiency, only solar panels are installed while the battery remains too expensive. Then, the installed capacities increase exponentially with greater values of self-sufficiency. This is mostly due to the need for oversized assets in order to overcome extreme events where the production is low during long periods of time. As a result, with a 100% self-sufficiency constraint, the battery is mostly underused so that the maximum exchangeable energy is large enough to avoid any new costly replacement with the aging model developed in this work.

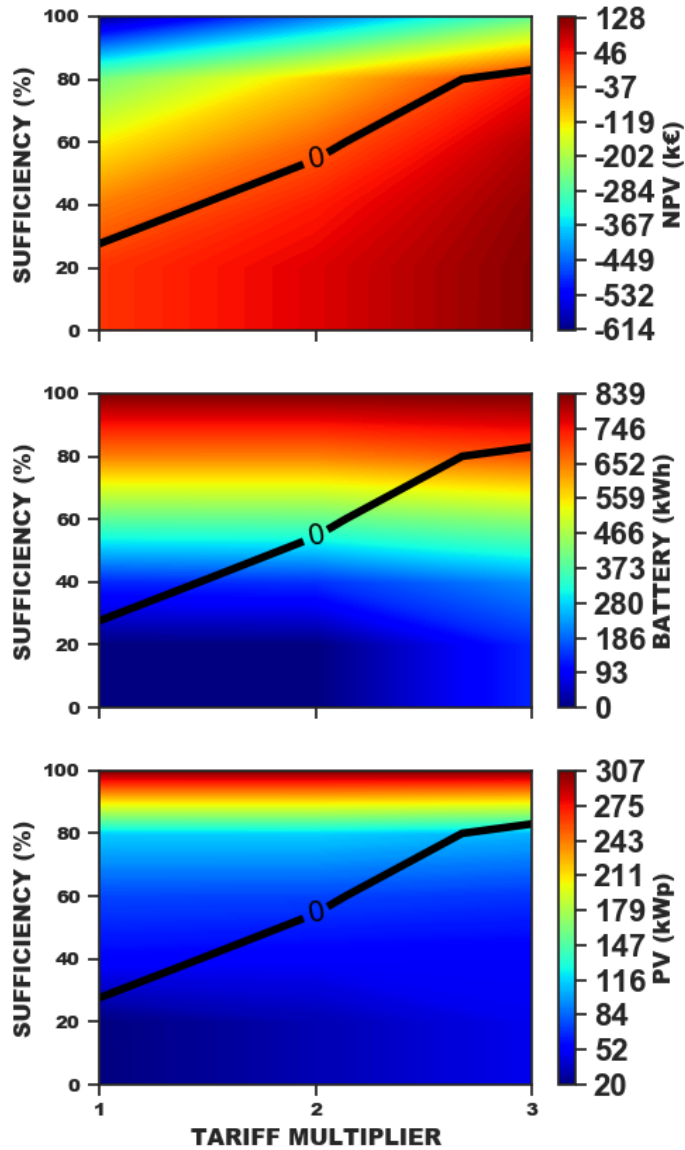


Figure 9: The net present value (top), the battery (middle) and the PV (bottom) cumulated capacities installed over the horizon as a function of the self-sufficiency and the tariff of electricity. The black isoline (NPV=0) delimits the area (under the line) where the DES is economically profitable over the 20 years (NPV greater or equal to zero).

In the second case, PV is installed even with current tariff and its size increases proportionally to the price of the electricity. In contrast, significant battery capacity is purchased over the horizon since the price has been multiplied by 3. In this case, the first investment is only made the 11th year as previously shown in section 5.3.

The results of this section could be summed up as follows:

- With current electricity tariff, a maximum of 30% self-sufficiency is affordable without loosing money over the 20 years. This result is obtained by only installing 35 kWp of PV.
- With current electricity tariff, a battery is installed with the self-sufficiency constraint greater than 40%. Then, the size of systems grows rapidly, especially between 80% and 100% where the components are oversized to overcome extreme events where the production is low during long periods.

- Without the self-sufficiency constraint, a significant battery capacity is installed over the horizon since the tariff of electricity has been multiplied by 3.

6. Discussion and conclusions

A generic multi-time scale model for both the design and operation of energy systems was presented in this work. The integration of the aging and replacement dynamic into MILP formulation was depicted. Two examples were run to demonstrate novelties that could be extracted from this approach. Results were then compared to more standard approaches which consider a single equivalent year for the optimization of the design.

It is shown from the previous sections that it pays to control aging as the optimal solutions from the proposed multi-time scale model give the best economic results: the difference goes up to 20% of the total cost in some cases. This cost improvement is made possible because the multi-time scale model includes the interaction between design and operation with investment options at every year. Indeed, aging of the battery and thus, the number of replacements are controlled over the horizon, which is not possible with method 1 and 2. Moreover, method 3 gives more flexibility to the design of the DES as it can accommodate to input parameters evolution over time: the size of systems could be modified along the horizon by taking full advantage of the new information available. Furthermore, more than only optimizing the size of system, the multi-time scale approach also determines the investment strategy over the horizon. This latter point seems to be interesting for industrial who are willing to know when would be the best moment to invest in order to maximize profitability. Again, this feature could not be addressed by standard methods. Finally, even with the multi-time scale approach, a battery is installed over the horizon whether the self-sufficiency constraint is greater than 40% or the price of electricity is multiplied by 3.

Unlike [11] and [12], the multi-time scale formulation focuses on the interaction between the investment and the operation which is, to the best of the authors' knowledge, rarely addressed in the literature. For the sake of simplicity, the equipment were assumed to be entirely replaced with the modeling developed in this work and no additional investment is made possible. This latter point is definitely a weakness of the model and future work need to be conducted in that direction to increase the value of the approach. Furthermore, the study was conducted in a deterministic framework whereas the real problem is profoundly stochastic: investment and operation decisions have to be made without perfectly knowing the future. However, the aim of the study was to make a first evaluation in a deterministic framework to assess the cost reduction potential of the multi-time scale approach before going into more realistic modeling with uncertainties. In order to include the stochastic nature of the problem and apply the methodology to more complex energy systems, computational times need to be reduced and further resolution methods have to be explored (the better performances of method 3 are obtained at the cost of greater computational time with 24h long calculation where method 1 is run in only 5 min and method 2 in 15 min). For instance, the decomposition methods developed by [15] seems to be a great candidate to address this challenge.

Despite these aforementioned limitations, it seems that the multi-time scale approach could be a promising direction in order to improve the income of a given project when energy rates are low and standard strategies fail to find out a profitable design. The model has proven to be a relevant approach and this work could be seen as a starting point for whoever would be interested in the integration of the interaction between investment and operation in more general energy models and complex analysis.

7. Acknowledgments

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A. Appendix

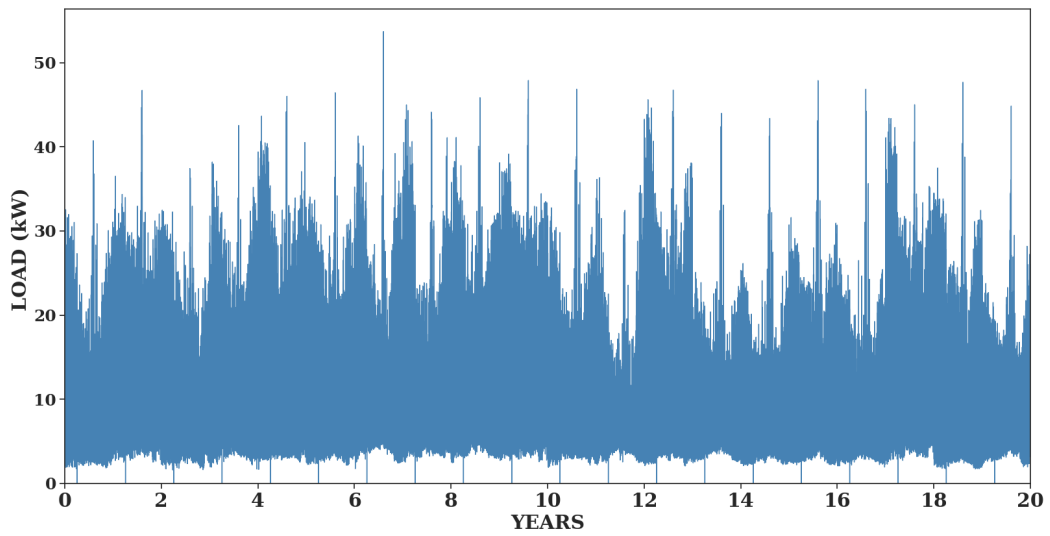


Figure 10: Time-series of energy demand over the 20 years.

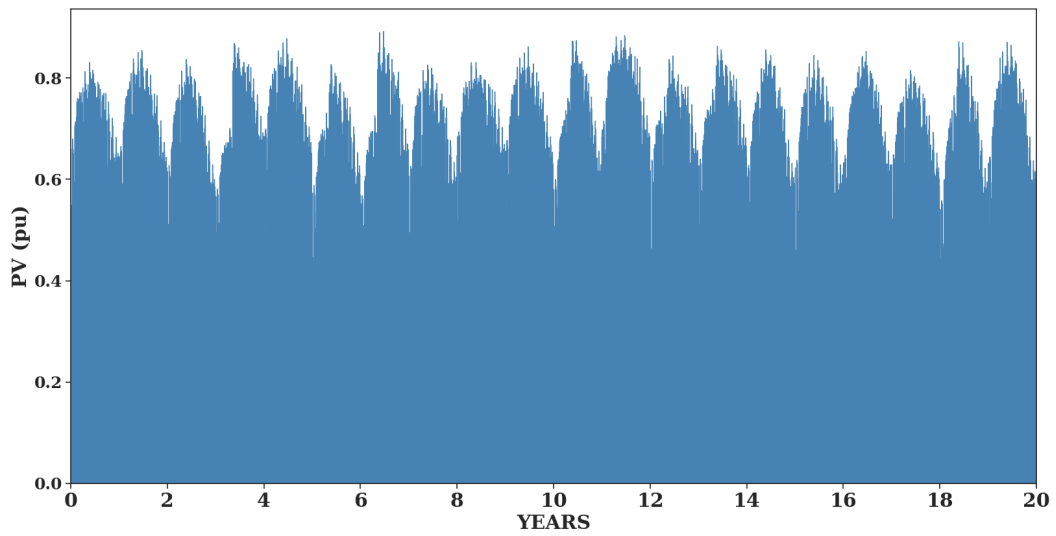


Figure 11: Time-series of normalized PV production over the 20 years.

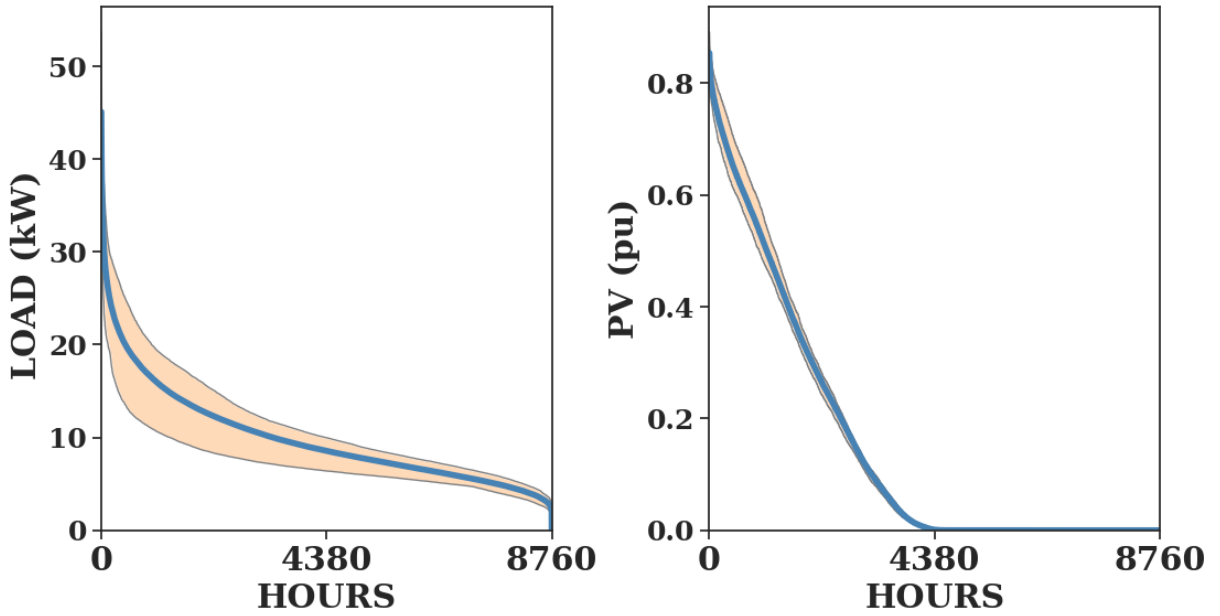


Figure 12: Duration curves for the energy demand (left) and PV production (right) for each year. The mean value is depicted in blue in the figure. The orange area corresponds to the min/max envelope over the 20 years.

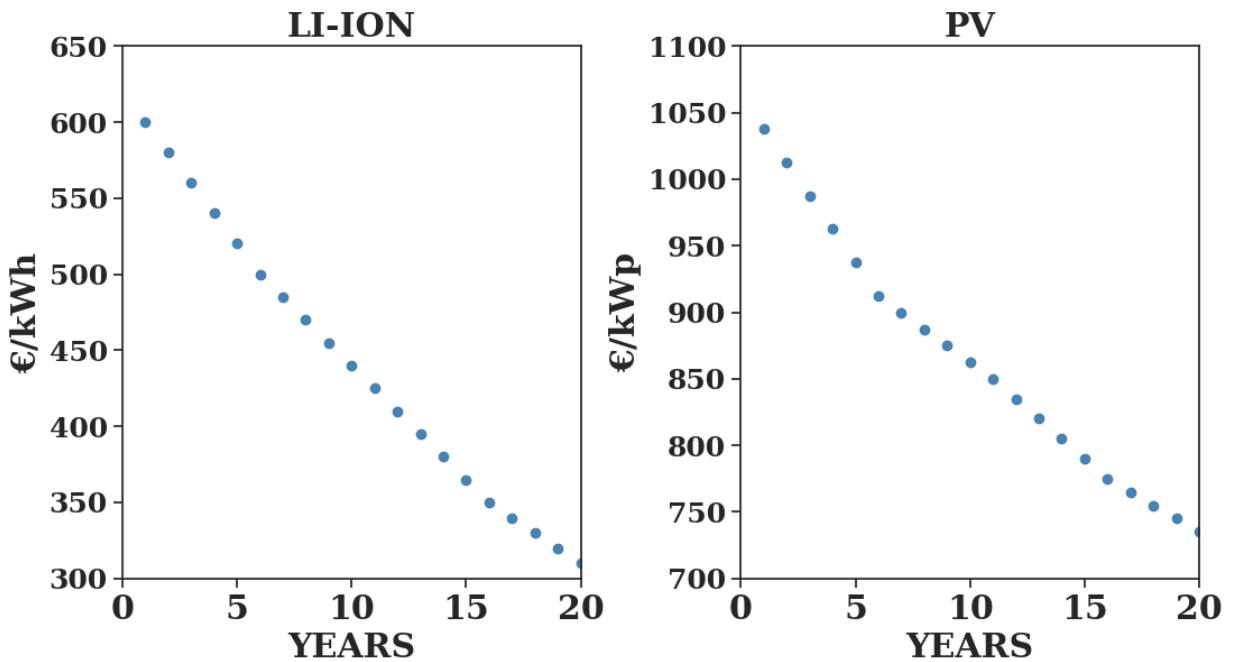


Figure 13: Time-series of battery and PV investment cost over the 20 years.