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Matching intermittent electricity supply and demand with electricity storage - An optimization based on a time scale analysis

Arthur Clerjon^{a,*}, Fabien Perdu^a

^a*Univ. Grenoble Alpes, CEA Liten, F-38000 Grenoble, France*

Abstract

The rising share of Variable Renewable Energy Sources (VRES) in the electricity generation mix leads to new challenges for the whole energy system. It especially raises technological issues to handle variability and to match electricity load with supply at all times. This study introduces a new methodology to quantify the relevance of different electricity storage technologies, based on a time scale analysis. It additionally provides an understanding of how electricity storages work in combination to handle variable load and intermittent generation. First, we set up a simple model of variable production, fluctuating over a single time-scale. This analysis provides figures of merit for electricity storage and curtailment. Second, we simulate the collaboration and competition behavior of various storages with a dual time-scale signal. Then, results are compared with the optimization of an energy system with real variable electricity supply and consumption time-series. We eventually highlight the trade-off mechanisms between the storage efficiency and its investment cost.

Keywords: Energy storage, Flexibility, Time scale, Intermittent Renewable Energy Sources, Energy system optimization

*Corresponding author

Email addresses: arthur.clerjon@cea.fr (Arthur Clerjon), fabien.perdu@cea.fr (Fabien Perdu)

1. Introduction

France aims to massively develop intermittent renewable electricity sources — mainly photovoltaic (PV) and wind power. Meanwhile, decarbonized dispatchable power plants are declining. These changes call for a greater need for “*flexibility*” in the electricity system, while removing the levers that historically provided it. On the international stage, this ambition is driven by prospective scenarios like IRENA’s *Global Energy Transition: A Roadmap to 2050* [1].

One of the major challenges of the energy transition is therefore to identify and assess new flexibility means that will guarantee electricity production and consumption balance. Of course, this question depends on the penetration rate of intermittency, the localization, the consumption patterns of electricity. Depending on these parameters, this balance can be achieved in various ways: it could be through electricity production and demand management, industrial load shifting, interconnections with neighboring countries, production oversizing or energy storage in different forms (chemical, mechanical, electrochemical, thermal). In this context, a key question is to determine the most relevant areas of use for each of these technological solutions and understand how they should be used in combination. Within this overall problem, the potential of electricity storage is a full part topic.

The study presented in this paper focuses on the potential of electricity storage and production oversizing to make sure that both electricity generation and consumption concur at any time. We deliberately narrowed the scope to part of the energy system — the electricity vector, electricity storage — to focus on their field of use. As further work, analyses conducted here on the electricity system would be extended to other energy carriers and flexibility solutions.

To properly assess the potential of electricity storage to manage a large deployment of intermittent energy sources, it is essential to model the interactions with the rest of the energy system — at least with the production means and electricity consumption. The main contributors to these research belong to the

energy planning community. This vast research field addresses numerous issues that relate with the development of energy systems, their sizing and investment schedule. To do so, many tools — *energy models* — have been developed. They differ by their level of complexity, their geographical perimeters, the time scale of the prospective, the level of detail of the technological models, among others. Of all issues, the deployment of new flexible systems is a central one. The 2015 JRC Report [2] presents a broad review of the models developed by the Energy Planning Community to describe the challenges of the growing need for flexibility.

After reviewing the literature of energy system and storage expansion planning (Haas et al., [3], Koltsaklis et al.,[4]), interacting with the open energy modeling community (OpenMod, [5]), examining the different methodologies developed (Cuisinier et al., [6]), we observed that most research efforts are focused on optimizing the sizing, investment and operation of a given energy system at different horizons. These approaches enable to assess the evolution of a system, to find the best decision-making in an uncertain environment [7, 8, 9]. Nevertheless, if these methodologies allow to determine the best possible combination of flexible solutions to optimize given criteria, they are less adapted to the analysis of the interactions between the different parts of the system.

In other words, most energy models are built on a common ground. Depending on the research question, the methodology will differ and so will the complexity the tool. On the one hand, energy planning models can assess an optimal combination of flexibility solutions, and to create, for example, energy transition scenarios. For the French territory, this has been done by RTE [10] or the CIRED institute [11], among others. On the other hand, the use of fast-running models launched several times allows parametric analyses to be performed. It provides field of relevance of each of these solutions and enable to grasp the key elements for understanding the energy system. It is notably the pathway followed by Sepulveda et al. [12], who assess the potential of long-duration storage, depending on their cost, efficiency and electricity cost. On

a similar note, Heggarty et al., [13] focus on the multi-temporal aspect of the flexibility need. He underlines, alongside with a previous study [14], the importance of distinguishing the different flexibility requirements, depending on the duration time-scale: day, week or year scale.

The study reported here is part of a larger research project [15], which aims to evaluate the impacts of a massive deployment of variable renewable energy sources on the French energy system and to assess the potential of energy storage solutions to handle it. All analyses we have carried are sharing a common concept: the *time-scales* analysis of intermittency. Based on a *wavelet decomposition*, it enables a quantitative description of the intermittency. We quantify the need for flexibility for each time-scale, ranging from an hour to a year. Depending on the intermittency of electricity production, we evaluate the potential of electricity storage to make production and consumption concur without dispatchable power plants. Additional details have been published in [14].

Here, we present the results of a second analysis. After assessing the potential of various electricity storages depending on their time-scale usage (daily, weekly, seasonal) in [14], we now investigate the inter-dependencies between storages to show how different technologies can work in conjunction.

This work focuses on the functioning of the electrical system in order to understand the complementarity mechanisms of the different storage technologies. However, several studies [16, 17, 18] have highlighted the potential of the coupling between electricity and heat vectors on the need for flexibility, and this question will be the subject of a future study.

Based on a Linear Programming (LP) approach, we present a methodology that provides *figures of merit* to compare different systems according to their characteristics. In this way, we are able to characterize and quantify, for example, the tradeoffs for a storage between investment cost and efficiency. Applied to the French territory case-study, we give insights to a number of questions:

- How does storage compete with production oversizing and excess electricity curtailment?
- Which is the optimal storage for a given time-scale?
- Will optimal storage for long term also handle shorter time-scales?

The *optimization criteria* used in this work is the total cost of the energy system. However, the methodology developed aims to remain general and could be applied to different criteria, such as the Global Warming Potential or the primary energy consumption.

2. Methodology

2.1. Assumptions

This study aims to depict the trade-off between electricity storage efficiency and the investment costs of all the energy system components. We want to provide orders of magnitude and compare each flexibility strategy with a common framework.

For those reasons, we reduced the number of parameters of the model to a minimum — the key ones —, using models with a low level of details. The following points set the framework of the study.

1. *Consumption is 100% satisfied.* This is made possible through electricity storages, electricity generation oversizing and curtailment. We do not consider demand-side management or dispatchable production.
2. *Copper plate approach:* Only the electricity vector is modeled. We do not consider grid losses. We assume a perfect match between production and consumption, wherever electricity is produced.
3. *Electricity storages characteristics:* Storages are defined by a charge efficiency η ; a calendar lifetime T_{life} and an investment cost. We do not consider self-discharge, aging or response time.

4. *Electricity generation characteristics:* We only consider electricity cost in euro per unit of energy produced that account for CAPEX and OPEX.

2.2. Input data

The results obtained are compared with electricity storage technologies described in Tab.1. It includes Li-ion batteries, Power-to-Gas through the hydrogen vector (*Hydrogen*) and Pumped Hydro-electricity storage (*PHS*). For hydrogen storage, we consider steel tanks for stationary purposes. We consider an overall energy cost for the French power generation system. Based on Levelized Cost Of Energy (LCOE) analysis [19, 20, 21], we choose an energy cost of $60 \text{ €/MWh}_{\text{produced}}$. In the following methodological description we will refer to this cost by γ_3 .

Table 1: Electricity storage characteristics. Input data used for the simulations.

Component	Investment cost		T_{life} (year)	Efficiency η (%)	Ref	γ_E $\text{€} \cdot (\text{MWh}_{stock} \cdot \text{yr})^{-1}$	γ_P $\text{€} \cdot (\text{MW}_{out} \cdot \text{yr})^{-1}$
	$\text{€/kWh}_{el,stock}$	€/kWh_{el}					
Li-ion	300	300	15	85	[22, 23, 24]	2.0×10^4	0^2
PHS	165	2600	60	80	[23, 24]	2.7×10^3	4.2×10^4
Hydrogen				30	[25, 26, 27]	1.2×10^3	3.7×10^5
H_2 tank	10.5		20	100			
Electrolyzer		725	1.14^3	65			
Fuel cell		5785	11.4^3	45			

Power time series are provided by the French Transmission System Operator ¹. We use 7 years, from 2012 to 2018 with one data registered every 30 minutes.

2.3. Model and tool description

To make sure that electricity production meets demand at all times, the variability of the energy system needs to be closely studied. Based on results previously published in [14], we are using in this manuscript the concept of

¹RTE, www.rte-france.com/fr/eco2mix/eco2mix

²Batteries both have an energy and a power capacity. Once the investment is made to size the device in energy, the investment for the power share is 0.

³Electrolyzer and fuel cell are defined with a continuous lifetime. Other lifetimes are calendar.

wavelets to describe and distinguish the various time-scale of the intermittency, from hourly to seasonal fluctuations. Similarly to a Fourier transform, a wavelet decomposition enables to separate a signal into components of different time scales. But in addition, wavelets retain a temporal information from the decomposed signal and enable, for example, to locate in time when occurred the biggest daily fluctuation of electricity consumption. The principle of the wavelet decomposition is sketched in Fig.1, where we see a signal filtered at four different time-scaled — which leads to a very imperfect approximation. We have shown in [14] that the input time series used — with one data recorded every 30 minutes — can be decomposed over 15 time-scales, ranging from 45 minutes to one year⁴ without information loss.

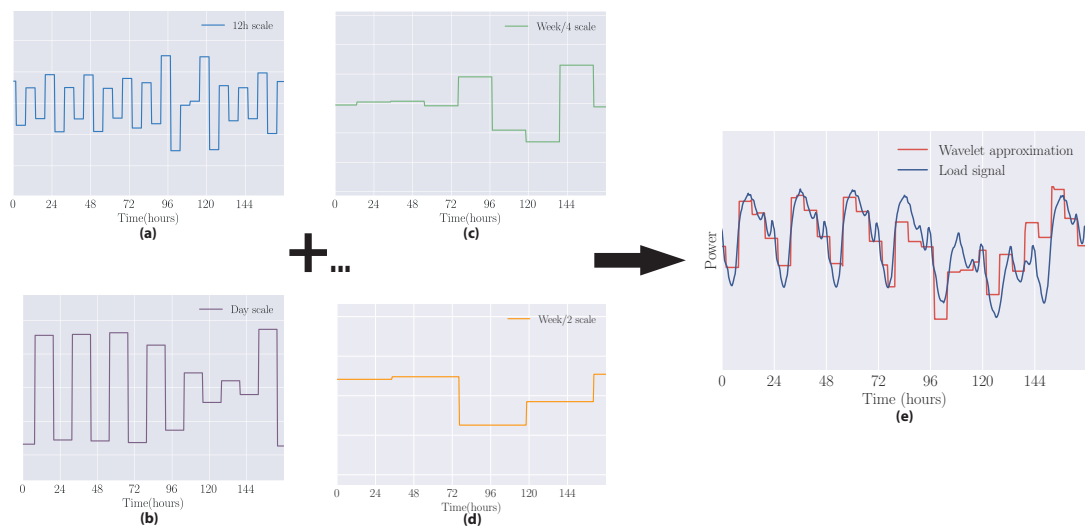


Figure 1: Sketch of the wavelet decomposition. Wavelet signals of time scale $\Delta T=12$ hours (a), 1 day (b), week/4 (c) and week/2 (d) are summed and placed on top of the original signal (e). Shorter time scales are missing here to show an imperfect approximation.

There is no need to go into more technical details for the study reported here. Square wavelets, as depicted in Fig.1, are simply a basis to model inter-

⁴The set of wavelets is built with three “mother wavelet”: Year, week and day. They are each recursively divided by two as “daughter wavelet”. The total set of wavelets covers time-scale from 45 minutes to one year and allows reconstructing any given signal. It makes a total of 15 different time-scales.

actions between several time-scales. Additional details are though available in [14, 15].

The energy system considered all over the study includes two electricity storage devices. We prescribe an electricity load and supply. The electricity is either stored, curtailed, or directly consumed. The supply can be oversized (i.e. total yearly supply is larger than total yearly load), only its shape is determined – we denote the oversizing factor by α .

The energy system is modeled with linear equations and the optimization problem is solved using the software *GAMS* with the OSICplex solver.

2.4. Global framework

We investigate the interdependencies of the variability time-scales. To get an intuitive grasp of the main trends, we first consider two “toy models” with single and dual time-scale, and then the real situation with entire signals. This paper is therefore divided into three steps:

1. We consider input time-series where electricity production varies over a single time-scale and consumption is assumed constant, as sketched in Fig.
2. These fluctuations depict a winter / summer photovoltaic production. For this very specific and simple case, the Simplex algorithm has been solved by hand. In this way, we managed to calculate an analytical solution that includes the dependence on input parameters.

The methodology is further developed in section 3

2. Then a second time-scale is added, representing daily and yearly variations – see section 4. The problem is now solved using GAMS and the OSICplex solver, which provides a numerical solution.

Those first two models are idealized descriptions for a deeper understanding of the basic phenomena.

3. Eventually, the previous results are compared with the analysis of real intermittent signals. We refer to it as *full signal* (section 5). Note that the wavelet transform we are using enable to decompose a signal over 15 time-scales.

Those three stages are presented in the three following sections.

3. Single time-scale

3.1. Method

We consider a constant electricity load ($= 1$), whereas the input supply has a *charge-discharge shape*, as depicted on Fig. 2. Average value of electricity production and demand are equal before oversized of the production by a factor α .

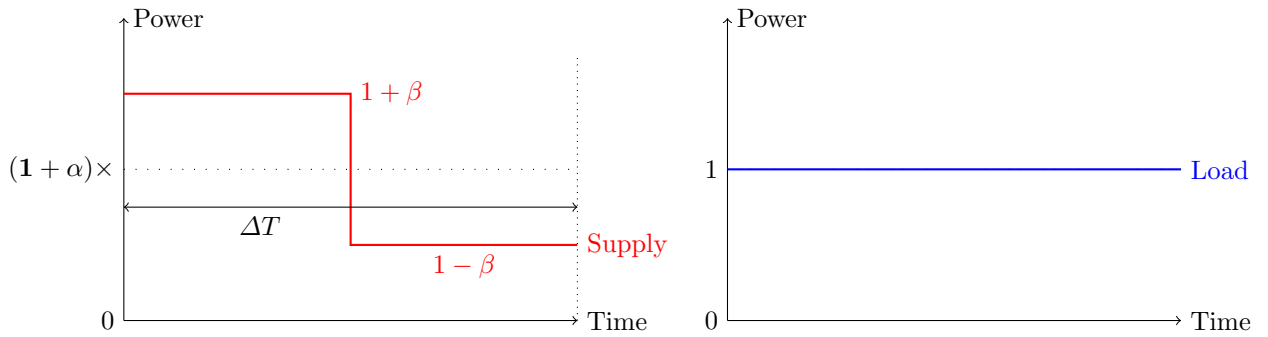


Figure 2: Input signals of the simulation with a single characteristic time-scale.

The energy model includes two electricity storages. We define their annual investment cost per unit of energy and power as $\gamma_{i,E}$ and $\gamma_{i,P}$, such that storage cost is

$$Cost_{storage,i} = \gamma_{i,P}P_i + \gamma_{i,E}P_i\frac{\Delta T}{2} \quad (1)$$

with P_i the discharge power of storage i .

We generalize this definition and introduce a global γ_i such that

$$\gamma^i = \gamma_{i,P} + \gamma_{i,E}\frac{\Delta T}{2} \quad (2)$$

Regarding the electricity generation cost:

$$Cost_{production} = \alpha\gamma_3\bar{P} \quad (3)$$

where γ_3 is the cost of electricity generation per unit of energy produced. $\bar{\mathbf{P}}$ is the average value of the electricity load. Here $\bar{\mathbf{P}} = 1$ MW.

The Objective Function can be written therefore such that

$$Cost = \gamma_1 P_1 \frac{\Delta T}{2} + \gamma_2 P_2 \frac{\Delta T}{2} + \alpha \gamma_3 \bar{\mathbf{P}} \quad (4)$$

Storage characteristics and γ_i are listed in Tab. 1.

3.2. Results and discussion

We calculate analytic conditions — detailed in the *Supplementary Information* — to determine which is the optimal solution. However, the solution depends on β , the level of variability. As the general case is complex, we only provide results for the extreme cases, $\beta \rightarrow 1$ and $\beta \rightarrow 0$.

1. $\beta \rightarrow 1$: Strong variability of the production signal

The optimal solution never implies curtailment, only the storage with the smallest figure of merit is used:

$$\text{Storage 2 is used} \iff \underbrace{\gamma_1 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_1}}_{\text{Storage1}} \geq \underbrace{\gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_2}}_{\text{Storage2}} \quad (5)$$

This is the figure of merit of a storage use. In this particular case of a strong variable signal, electricity curtailment cannot be an optimal solution. In fact, electricity production meets 0 for half of the time. Electricity consumption could not be satisfied without using electricity storages.

2. $\beta \rightarrow 0$: Small variability of the production signal

When $\beta \rightarrow 0$, oversizing the production by a factor α and curtailing the excess electricity can be relevant in certain cases, while storing it is

preferred in other.

$$\text{Electricity is stored} \iff \begin{cases} \gamma_1 \frac{\Delta T}{2} \leq \gamma_3 \\ \text{or} \\ \gamma_2 \frac{\Delta T}{2} \leq \gamma_3 \end{cases} \quad (6)$$

In that case, a single storage is used:

$$\text{Storage 2 is used} \iff \frac{1}{\eta_1 + 1} \left(\eta_1 \gamma_1 \frac{\Delta T}{2} + \gamma_3 \right) \geq \frac{1}{\eta_2 + 1} \left(\eta_2 \gamma_2 \frac{\Delta T}{2} + \gamma_3 \right) \quad (7)$$

We can extract from Eq.(5) and Eq.(7) valuable comparisons between two storages. In particular, we calculate ΔT_{eq} , the time-scale of charge - discharge from which a storage is more relevant than the other – from the optimization stand-point. To do so, we have to introduce $\gamma_{i,E}$ and $\gamma_{i,P}$ in the calculation because the share in energy and power depends on ΔT .

In such case, γ_i is replaced such that

$$\gamma_i \rightarrow \gamma_{i,E} + \frac{2\gamma_{i,P}}{\Delta T} \quad (8)$$

where ΔT is the time-scale displayed on Fig. 2.

$$\left\{ \begin{array}{l} \Delta T_{eq,\beta \rightarrow 1} = \frac{\gamma_3 \left(\frac{1}{\eta_2} - \frac{1}{\eta_1} \right) + 2(\gamma_{2,P} - \gamma_{1,P})}{\gamma_{1,E} - \gamma_{2,E}} \\ \Delta T_{eq,\beta \rightarrow 0} = \frac{2\gamma_3 \left[\frac{1}{1+\eta_2} - \frac{1}{1+\eta_1} \right] + 2 \left[\gamma_{2,P} \left(\frac{\eta_2}{1+\eta_2} \right) - \gamma_{1,P} \left(\frac{\eta_1}{1+\eta_1} \right) \right]}{\gamma_{1,E} \left(\frac{\eta_1}{1+\eta_1} \right) - \gamma_{2,E} \left(\frac{\eta_2}{1+\eta_2} \right)} \end{array} \right. \quad (9)$$

Equation (6) shows when oversizing the energy generation and curtailing excess electricity is more relevant than using electricity storages. We denote this specific time scale by $\Delta T_{\beta \rightarrow 0, curt}$.

$$\Delta T_{\beta \rightarrow 0, curt} = 2 \cdot \frac{\gamma_3 - \gamma_P}{\gamma_E} \quad (10)$$

Numerical application of Eq.(9) and Eq.(10): Li-ion batteries are compared with hydrogen storage: the former has a high investment cost in energy, the latter a high *power* investment cost, because of the electrolyzer and the fuel cell.

Results are summarized on Fig. 3. In particular, we observe that using Li-ion is preferable up to 2-6 days. In the case of a small variability, it would be more relevant to oversize the electricity production for longer durations. In the case of a strong variability, where electricity production can meet 0, hydrogen is preferable for long time-scales⁵.

⁵An interactive tool has been created on <https://fabienperdu.github.io/ElecStorageCost> for users to play with the features of their own storage technology. In addition, it compares the cost of storage with the one of electricity generation.

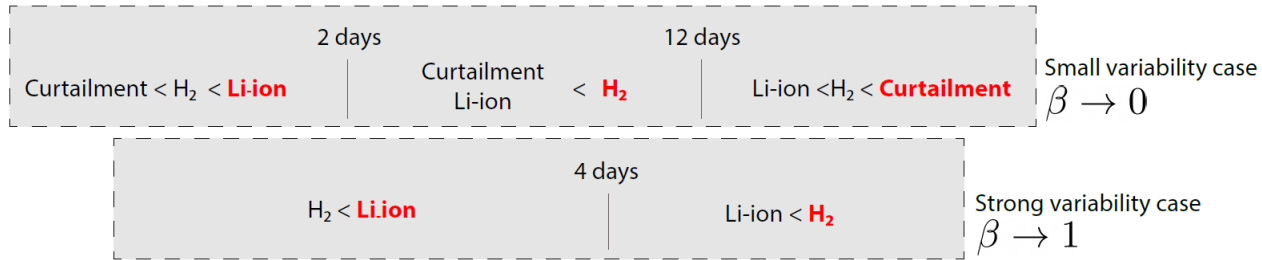


Figure 3: Calculation of ΔT_{eq} between the use of Li-ion, hydrogen or oversizing. Those results corresponds to the framework “*Single time-scale*”. It shows which is the most relevant technology to be used, depending of the time-scale usage. Warning note: the cost of the optimal technological solution does not appear. It skyrockets for long time-scales and strong variability.

These conclusions can be generalized into two principal points:

- The lower the variability, the more electricity production will be oversized. Conversely, the greater the variability, the more electricity storage with a low efficiency will be penalized.
- Depending on the storage duration, long term or short term, electricity storage does not require the same characteristics. Equation 5 shows that there is a trade-off between investment cost and efficiency. For short-term storage, the investment cost dominates the total cost. Conversely, for the long-term, it is the investment cost that prevails. It explains why Li-ion batteries are preferred for short-term storage, whereas hydrogen goes for longer durations.

4. Dual time-scale

4.1. Method

The previous section shows that for a single time-scale intermittent signal, only one storage technology is used. Here we investigate the co-existing domain of two technologies. To this end, we now consider a variable production with two time-scales, as drawn on Fig. 4: seasonal and a daily time-scale. We refer to the short term fluctuations as *day and night*, long term ones as *summer and*

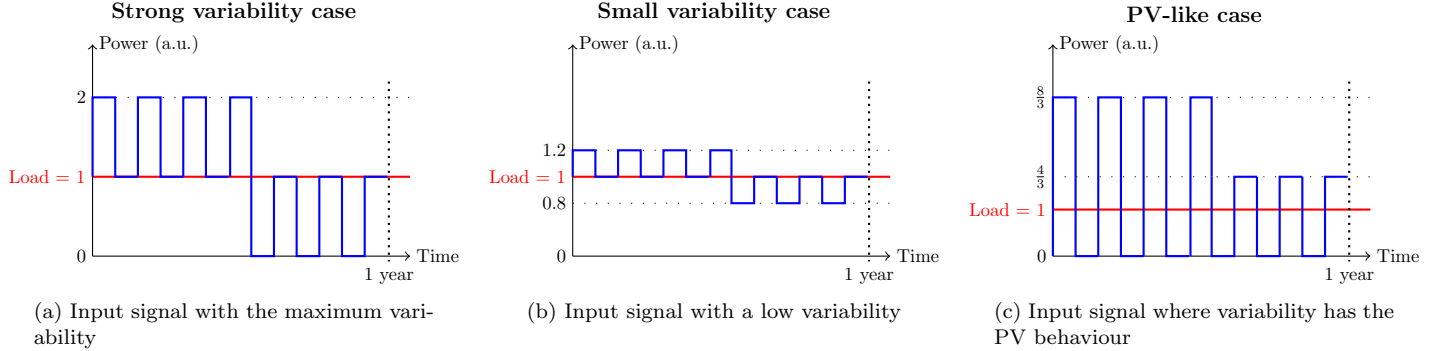


Figure 4: Input signals of the dual time-scales simulation described in 4. For readability concerns, we display only 7 days among the 365 of the signal. Electricity supply is the pseudo-periodic blue signal, Load signal is the constant value red value.

winter.

Simulations are performed with three different input signals, shown on Fig. 4. It accounts for different penetration rates of variability in the power generation.

We consider two hypothetical storage devices: one with a high efficiency, compared with another one with a low investment cost. To do so, we assign an efficiency of 85 % to the storage 1. It accounts for high efficiency devices such as Li-ion batteries or PHS. η_2, γ_1 and γ_2 are varying parameters such that

$$\left\{ \begin{array}{l} \eta_2 \in [0, 100\%] \\ \frac{\gamma_1}{\gamma_3} \in [10^{-1}, 10^7] \text{ (year}^{-1}\text{)} \\ \frac{\gamma_2}{\gamma_3} \in [10^{-1}, 10^7] \text{ (year}^{-1}\text{)} \end{array} \right.$$

For the sake of simplicity we assign $\gamma_P = 0$, since we cannot easily display results in a 5-dimension space.

The calculations return the following results:

- α , the *oversizing factor* of the electricity generation means. We prescribe as input signals *supply* and *load* with equal averages over the year. The supply can be oversized when compared with this initial average.
- $P_{charge,i}$ and $P_{discharge,i}$, the charge and discharge power of storage i .
- P_{curt} , the curtailed electricity power.

4.2. Results and discussion

We represent in Fig. 5 the results of the parametric analysis for the *small variability case*. This behavior is typical of the two other cases. This figure shows the set of parameters $(\eta_2, \gamma_1, \gamma_2)$ for which both or no storages are used to fulfill the electricity consumption. Obviously, as long as $\eta_2 < 80\%$, the optimal solution when $\gamma_2 \geq \gamma_1$ is not storage 2.

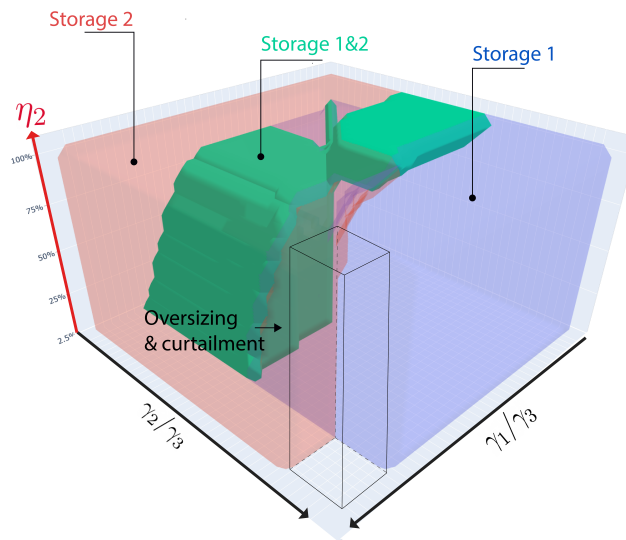


Figure 5: Computation made with the input signal presented on Fig. 4b, the *small variability case*. The red area corresponds to storage 2, the blue to storage 1. Where the space is green both storages are used in combination. Where there is no color, *Service* is fully provided by the oversizing.

In particular, we observe that a single storage can operate the total intermittency on its own. However, two storages can be used in conjunction with a large range of parameters: it is depicted by the green area in Fig. 5. When costs are too high, it became more relevant not to use storage but oversize the production to make sure that it is greater than the consumption at all times. It is represented by the rectangular cuboid in the corner of the figure.

Figure 5 is sliced with a constant efficiency of storage 2 $\eta_2 = 30\%$ (Fig. 6a). It corresponds with the efficiency of hydrogen. Figure 6b depicts a slice with a constant investment cost of storage 1, corresponding to the Li-ion batteries investment.

We investigate now further the area where both storage 1 and 2 are used in combination (green area). When both storages are used in conjunction, no electricity is curtailed. In fact, storage 2, when sufficiently low cost, behaves as an improved version of oversizing and curtailing. Among the three different cases, we observe two clusters of behaviour, represented on Fig. 7:

- **Fig. 7a:** Low cost storage 2 is charged during summer days and discharged during winter nights, while storage 1 is only cycling in winter. As such, storage 2 contributes to the service at both time scales. This behavior has only been observed for input signals of Fig. 4a and 4b, the strong and small variability cases.
- **Fig. 7b:** Storage 2 behaves similarly as in Fig. 7a. But this time, storage 1 is cycling everyday, all year long. It corresponds to the *PV-like case* described on Fig. 4c

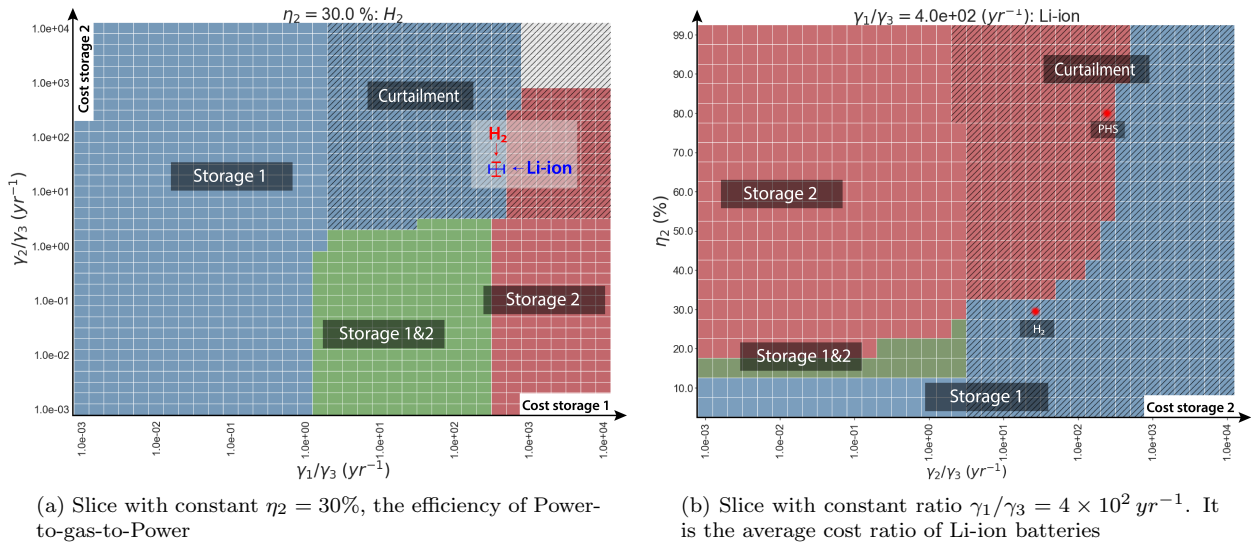


Figure 6: Slices of the volume of Fig. 5. It shows the domains where only *storage 1*, *storage 2* or both are used. One also notices in (a) that for expensive storages, the electricity consumption is only satisfied thanks to the power generation oversizing. This area is denoted by *curtailment*. Energy is also curtailed in the hashed area.

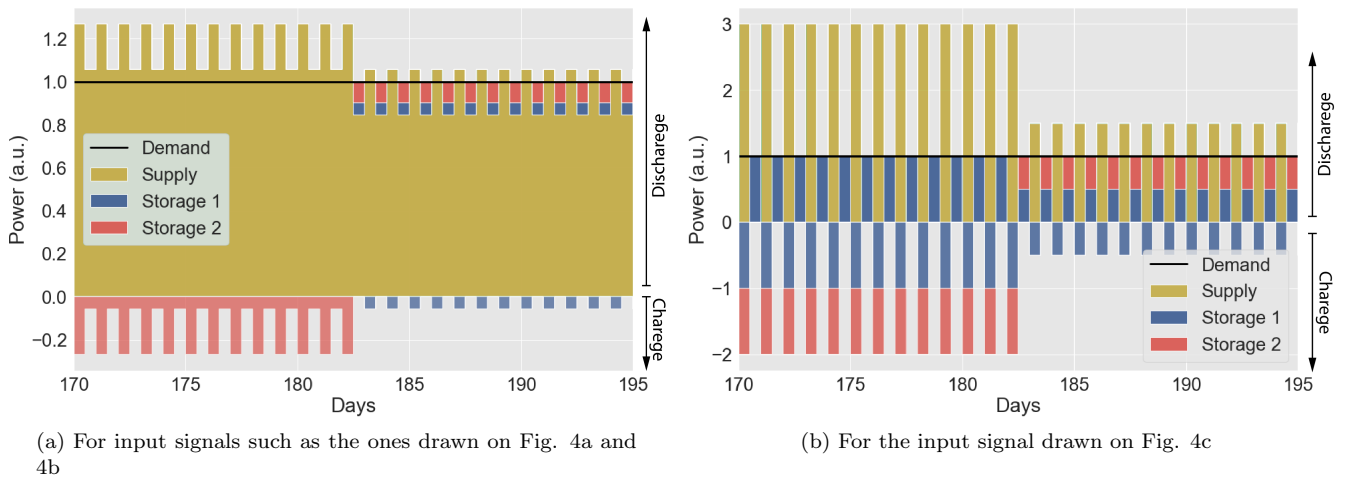


Figure 7: The two typical behaviours of charge discharge when the optimal solution requires to use both storage. The time series are centered on the summer/winter season change.

5. Full signals analysis

5.1. Method

We eventually simulate the behavior of the energy system with two storages using 7 years (2012-2018) of real *demand* and *supply* electricity time-series as input data. This analysis is carried in four steps, as illustrated by Fig. 8.

1. First, we create input signals based on electricity production and consumption time series such that:

- Four electricity generation means are considered: PV and wind power, nuclear and hydroelectricity that are dispatchable sources.
- We assume that dispatchable power plants generate a constant electricity supply.
- Electricity supply is normalized to the electricity demand. Thus

$$\begin{aligned}
 \text{Supply} = \text{Average load} \times [PV_{ratio} \times PV \text{ signal} + Wind_{ratio} \times Wind \text{ signal} \\
 (11) \\
 +(1 - PV_{ratio} - Wind_{ratio})]
 \end{aligned}$$

where *Average load* is the average annual electricity consumption. Index *ratio* range from 0 to 1 and refers to the share of the power system in the electricity generation mix.

2. Second, energy system with two electricity storages is optimized.
3. Then output signals are decomposed over 15 different time-scales using a wavelet methodology². From a practical perspective, this decomposition enables to quantify — for 15 time scales ranging from 45 minutes to one year — the flexibility need.

²The source code we developed for this analysis is available on GitHub: https://github.com/ArthurClerjon/wavelet_decomposition.

4. Eventually those results are analyzed to determine which system — from storage 1, storage 2, oversizing of the electricity production — provides the required flexibility for each time scale.

Let the *Service* be the total amount of energy provided by the storage and the production oversizing when the initial production is lower than the consumption.

$$\begin{aligned}
 Service &= \int_{Load > Supply} (P_{load}(t) - P_{supply}(t)) \cdot dt \\
 &= \sum_i \int_{Load > Supply} (P_{discharge,i}(t) - P_{charge,i}(t)) (dt) + \int_{Load > Supply} (\alpha P_{supply}(t) - P_{curt}(t)) dt
 \end{aligned} \tag{12}$$

For each of the 15 time scales, the distribution of *Service* between storage and oversizing calculation is detailed in the following box:

Service allocation calculation:

Equation 12 shows that the service is both provided by storage and the oversizing of the electricity production. Those contributions can be quantified such that

$$\text{Storage contribution} = \int_{\text{Load} > \text{Supply}} (P_{\text{load}}(t) - P_{\text{supply}}(t))^+ dt \quad (13)$$

$$\text{Oversizing contribution} = \int_{\text{Load} > \text{Supply}} (\alpha P_{\text{supply}}(t) - P_{\text{curt}}(t))^+ dt \quad (14)$$

$$\text{Service} = \text{Useful oversizing} + \text{Useful discharge}$$

Therefore

$$\text{Useful discharge} = \text{Service} \times \frac{\text{Storage contribution}}{\text{Oversizing contribution} + \text{Storage contribution}} \quad (15)$$

and

$$\text{Useful oversizing} = \text{Service} \times \frac{\text{Oversizing contribution}}{\text{Oversizing contribution} + \text{Storage contribution}} \quad (16)$$

Three different electricity generation mixes are compared here: two extreme cases, one fully photovoltaic and another one fully wind power. We additionally consider an hybrid-mix, the Ampere-like scenario³ It includes 25% of wind power and 10.5 % PV. For all cases we choose the same average load such that

$$\text{Average load} = 54 \text{ GW}$$

³Ampere is developed by the French TSO. It is a moderate VRES penetration scenario. Additional information are available in [28].

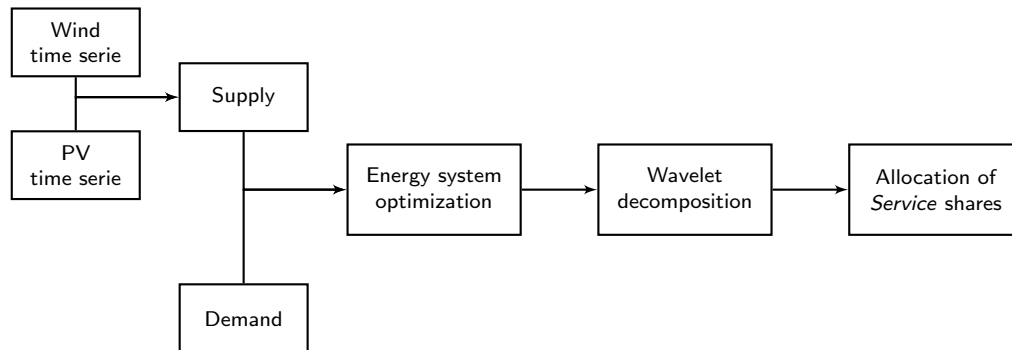


Figure 8: **Description of the methodology in four steps of the simulation carried with real time series.** First, the power generation signal is created. Second, with this input data, the energy system is optimized. Third, the output time series of the optimization are decomposed using the wavelet methodology. Finally, we analyzed what provides the required *Service* that matches the electricity demand and supply: storage 1, 2 or oversizing.

5.2. Results and discussion

Fig. 9 shows results performed for the residual demand of the three scenarios: 100% PV, 100% Wind and Ampere scenario. Two electricity storages are compared here, *Li-ion batteries* – the expensive and efficient storage – and power-to-gas-to-Power through *hydrogen* – the less expensive and less efficient one.

The analysis of Figure 9 shows how *Service* is allocated between Li-ion batteries, hydrogen, and oversizing. On the right-hand side of each subfigure is represented the total *Service* repartition. Then, the left-hand side figures represent the decomposition of the *Service*.

We start to analyze to right-hand side figures, the total *Service*. It shows that:

- The more intermittent the production, the more storage is developed. For example, in Ampère scenario, Figure 9c we see that most of the flexibility comes from the oversizing.
- When compared with the results of two previous models, the share of oversizing is here even greater, storage is less used.

Then, the Service decomposition analysis (left figures), can be done in two phases.

First, the general shape of the Service, the green dotted line. It highlights the main trends of the intermittent sources. For each time scale, it represents the total energy to be shifted per year because demand is greater than supply. This highlights the main trends of the intermittent sources. PV production (Fig.9a) shows a high variability on a daily and seasonal scale. On the contrary, wind generation (Fig.9b) has longer cycles from days to weeks. Concerning the Ampère scenario ((Fig.9c), the need for flexibility is strongest at the seasonal scale, mainly due to the strong variation in electricity demand between summer and winter in France.

Second, we can analyze the *Service* allocation between Oversizing, Li-ion batteries and Hydrogen.

- The comparison between Fig.9a,9b and Fig.9c shows that, the more intermittent the electricity production, the more efficient storages are developed. Conversely, the less intermittent the production, the more oversizing will be sufficient to provide the required flexibility.
- The optimal solution combines the use of both storages at various time scale. The two mechanisms presented on Figs 7a and 7b are at stake here.
- Additionally, we see that Hydrogen, the low cost and low efficiency storage prevales for the longer time-scales, whereas Li-ion is to be preferred for the shorter ones.
- With a lower H_2 storage cost, we would observe a more important use of this electricity storage means around the month, in line with what was observed with the previous *two time scale* model.

This simulation confirms the main trends that have been observed with the previous two models. However,15 different time-scales are mixed here, which

makes the analysis more complex, additional interactions between time-scales being now at stake.

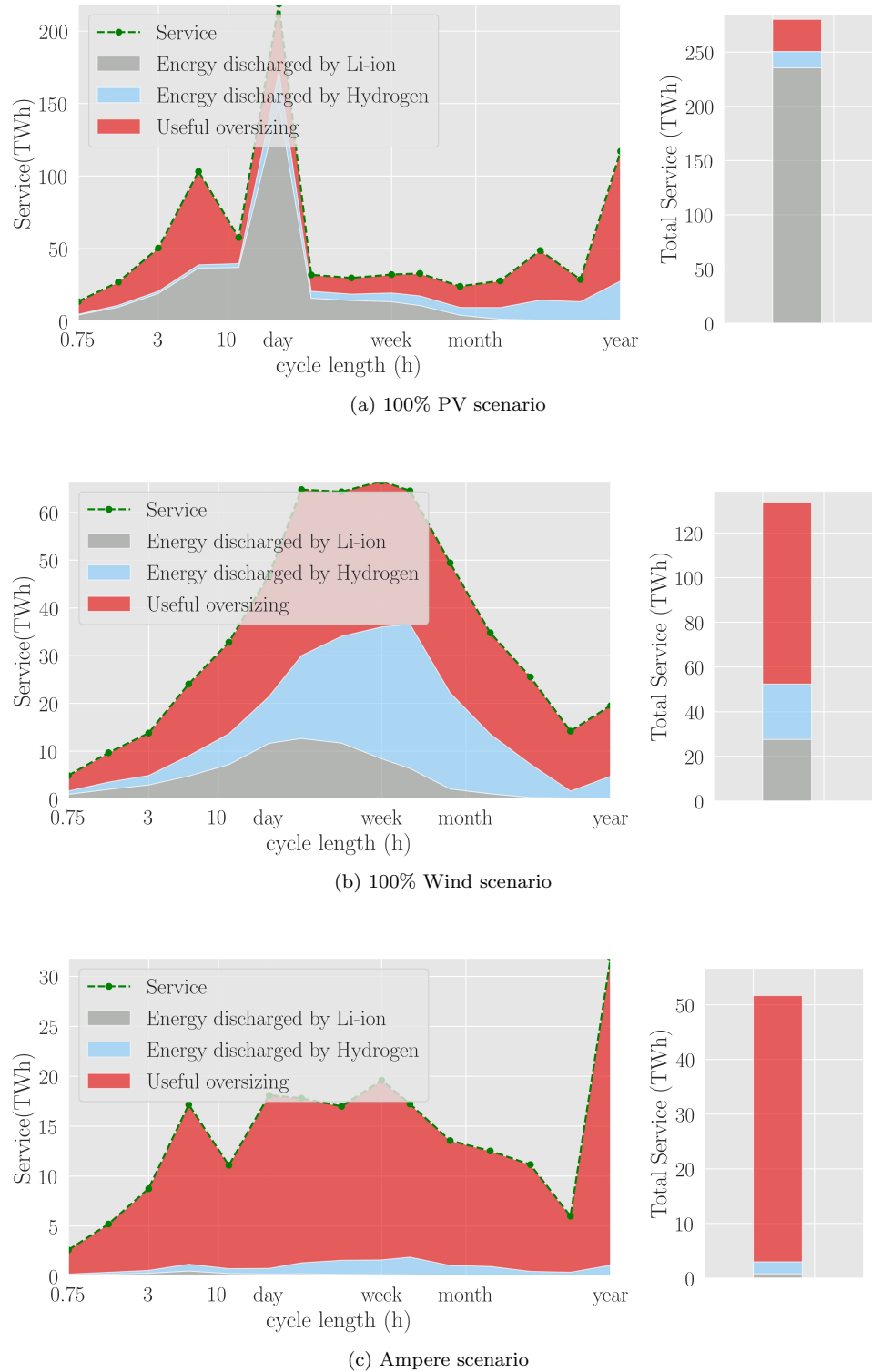


Figure 9: *Service* calculated for three different scenarios: 100% PV (a), 100% wind power (b), and the Ampere electricity generation mix (c) that includes 25% of wind power and 10.5% of photovoltaic. Left-hand figures depict *Service* decomposition over the 15 time-scales, right-hand figures the total *Service*, all time scales combined. *Service* is the amount of energy that is provided over the year to fill the shortage when *electricity production* < *consumption*. Those figures show the contributions to the *Service* of two storages and the oversizing of the electricity production.

6. General discussion

This study aims to provide an *understanding* of electricity storage integration within the context of a variable electricity generation. It is not intended to create a comprehensive energy transition scenario, but to provide *orders of magnitude*. We are considering simple models with the following limitations:

- We are working with energy production and consumption time series; energy consumption and production are known in advance. Therefore, the solution would be a lower bound of a simulation where future is unpredictable.
- Because time-series have a resolution of 2 data every hour, we cannot tackle grid stability issues
- The energy generation mix is established and cannot change. Only electricity storages facilities can be modified.
- There are no dispatchable power plants included in our simulations. As a matter of fact, they are by far the cheapest flexibility means and would supplant electricity storages.

7. Conclusion

This article investigates how electricity storage can handle the intermittency generated by a strong deployment of variable Renewable Energy Sources. Starting from a very simplified model of variable electricity generation signal, we have been able to provide figure of merit for electricity storage and curtailment. We prolonged those analytical solutions by optimizing more complex model, including a second time-scale. Results have eventually been compared with the analysis of 7 year real time-series over three energy generation scenarios: two extreme cases, 100% PV and 100% wind power mixes, and Ampere, a scenario with 35% of intermittent energy sources. We emphasize the fact that the guidelines provided by the first two toy-models are confirmed by this latest most

detailed modeling. This methodology provides a better understanding of the *trade-off between storage efficiency and its investment cost*. Moreover, those different approaches enable a better anchoring of our results. In particular, we note that:

- Expensive electricity storage with a good efficiency — like Li-ion batteries — will be dedicated to handle the short term intermittency (up to a few days).
- On the opposite, longer time scales can be managed by oversizing the production and curtailing excess electricity.
- In case of high level of variability, a low cost and low efficiency storage, like hydrogen, is preferred over curtailment for long time scales.
- In the specific case of strong intermittency, handling the long term variability with electricity storage has a dramatic cost. Regardless of the technology.
- When there are two different time-scales and two storages involved, the long-term one can also support for the short term fluctuations. The opposite situation is impossible.

This analysis is performed using economic costs. However, apart from numerical applications, the three models are generic and the methodology can be applied at any other indicators such as *embodied energy* [14] or *Global warming Potential*.

Directions for further research

This study highlights the limited interest of handling intermittency of a system only using electrical flexible means — electricity storage and production oversizing. It is especially true for long time scales. We saw that there is no appropriate strategy that can handle the seasonal variability of electricity consumption. In every case, the cost of electricity is multiplied by a factor of three.

It points out that other flexibility solutions must be investigated. First, in this work, the potential of dispatchable power plants is not evaluated. However, the complementarity between storages and dispatchable power plants is a research topic that should be conducted. It would answer questions such that “*With how many storage facilities and intermittent units can I replace a dispatchable unit?*”. *Pareto front* could be drawn between intermittent and dispatchable sources.

Second, the long term flexibility could also be provided with other energy vectors such as gas or heat. In fact, as thermal storage presents costs and efficiencies intermediate between Li-ion and hydrogen, its role in a coupled electrical-thermal energy system is worth being investigated.

Nomenclature

Definitions

Service: Total amount of energy provided to the grid when the initial electricity production is lower cannot satisfy the electricity consumption

Residual demand: Variable electricity consumption *minus* electricity production time-series

Load Electricity consumption

Curtailement Oversizing electricity generation means and curtailing excess electricity.

Indexes

T_{life} Calendar lifetime

el Electrical

$stock$ Stored electricity

out Output electricity

i_n Input electricity

Greek letters

η Round-trip electricity storage efficiency

$\gamma_{i,i \in \{1,2\}}$ Normalized investment cost of energy storages.

γ_3 Cost of energy generation per unit of energy produced.

α Oversizing factor of the initial electricity generation system

β Quantify the amplitude of a time-series variability. $\beta \in [0, 1]$

ΔT Storage time-scale of charge - discharge

8. Data Availability

Electricity generation and consumption time-series at the French scale are available online on the web page of the TSO: www.rte-france.com/eco2mix.

Declaration of competing interest

The authors declare no conflict of interests.

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