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Matching Intermittent Electricity Supply and Load with Energy Storage: an Optimization Based on a Time Scale Analysis

Arthur Clerjon and Fabien Perdu

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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] *CEA Liten, Grenoble, France, arthur.clerjon@cea.fr*

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 gives figure of merit for electricity storage and curtailment. Second, we simulate the collaboration and competition behaviour 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 optimisation

1. Introduction

A massive deployment of Variable Renewable Energy Sources (VRES) – PV and wind turbines, for example – is source of huge flexibility need. Different means can provide this required flexibility: electricity over-production and curtailment, storage, electricity network, management of dispatchable production and demand side management. Dispatchable production is by far the cheapest and most used flexibility mean today. However, only the first two solutions are investigated here: generation over-sizing and electricity storage.

The question of electricity storage has only been quantitatively addressed recently in the literature. Hass et al [1] highlighted that "*only the last [7] years research efforts have been put in [expansion planning for energy storage]*". In contrast with the *Global Expansion Planning* approaches that Haas reviewed, [2, 3, 4, 5] are considering a closed energy system with an intermittent electricity production. Then, they evaluate the relevance of electricity storages from an *Energy Return On Investment* stand point. It sheds light on the electricity storage mechanisms with a high share of VRES. Within a similar context, this study follows their approach with a new methodology. In particular, we investigate in detail the different storage time-scales, from one hour to one year.

Intermittency is source of strong constraints on the energy system. As a result, it is important to quantify how and to which extend the system is impacted. On the one hand, variability of electricity signals – generation and consumption – has different time-scales due to human rhythms, meteorological and climatic cycles. Additionally, fluctuations of load and supply are not uncorrelated: it happens, in temperate climates, that there is no wind during cold winter weeks. As a result, flexibility needs present different time scales: daily, weekly and seasonal fluctuations. On the other hand, storage technologies are characterized by a set of parameters such as efficiency, life-time, investment costs. Therefore each storage is more suitable for a specific usage, it must be considered.

We propose here a new methodology to quantify the flexibility requirements involved by the deployment of variable Renewable Energy Sources, and to optimize how electricity storage can tackle this intermittency. It is done for different time scales, from hour to year. The *optimisation criteria* is the total cost of the energy system. However, the methodology would remain the same if the cost was an embodied energy or a Global Warming Potential indicator. Our methodology provides *figures of merit* to answer the questions related to the trade-off between investment cost and storage efficiency:

- How does storage compete with production over-sizing 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?

2. Methodology

2.1. Assumptions

This study aims to depict the trade-off between electricity storage efficiency and the investments costs of all the energy system components. We want to provide orders of magnitude, to this end we set-up a simple energy model:

1. *Consumption is 100% satisfied.* This is made possible through electricity storages, electricity generation over-sizing and curtailment. We do no consider demand-side management or dispatchable production.
2. *Copper plate approach*: Only the electricity vector is modelled. 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 life-time T_{life} and an investment cost.We do not consider self discharge, ageing or response time.
4. *Electricity generation characteristics:* We only consider here a calendar life-time, an investment cost and a capacity factor. No response time or minimum power.

2.2. Input data

Power time series are provided by the French Transmission System Operator [*]. We use one year with one data registered every 30 minutes. 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 tank reservoir for stationary purposes. We consider an overall energy cost for the French power generation system. Based on Levelized Cost Of Energy (LCOE) analysis [6, 7, 8], we choose an energy cost of $60\,€/MWh_{\text{produced}}$. In the following methodological description we will refer to this cost by γ_3.

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[*] RTE, `www.rte-france.com/fr/eco2mix/eco2mix`

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

Component	Investment cost $€/kWh_{el,stock}$	 $€/kW_{el}$	T_{life} (year)	Efficiency η (%)	Ref	γ_E $€ \cdot (MWh_{stock} \cdot yr)^{-1}$	γ_P $€ \cdot (MW_{out} \cdot yr)^{-1}$
Li-ion	300	300	15	85	[9, 10, 11]	2.0×10^4	0 †
PHS	165	2600	60	80	[10, 11]	2.7×10^3	4.2×10^4
Hydrogen				30	[12, 13, 14]	1.2×10^3	3.7×10^5
H_2 tank	10.5		20	1			
Electrolyzer		725	9 ‡	0.66			
Fuel cell		5785	25	0.45			

2.3. Mathematical and computational tools

We decompose power time series by characteristic time scales using Haar wavelet analysis. Wavelet analysis is extensively described by Mallat in [15]. We have detailed this decomposition in the reference** [2].

Unlike a Fourier series decomposition, wavelets retains a temporal information from the decomposed signal. The set is built with 3 *"mother wavelets"*: Year, week and day. They are each recursively divided by two as *"daughter wavelets"*. The total set of wavelets covers time-scale from one hour to one year and allow to reconstruct any given signal. It makes in total 15 different time-scales.

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 over-sized (i.e. total yearly supply is larger than total yearly load), only its shape is determined – we denote the over-sizing factor by α.

The energy system is modelled with linear equations and the optimization problem is solved with the Simplex algorithm. When the system is too complex to be solved by hand, we used the software *GAMS* to solve the optimization problem.

2.4. Global framework

We investigate further the interdependencies of the variability time-scales. To get an intuitive grasp of the main trends, we first consider toys model with single and dual time-scale, and then the full situation.

1. The electricity production varies over a single time-scale. It could depict a winter / summer photovoltaic production. Additional details are found in section 3.
2. Then a second time-scale is added, representing daily and yearly variations – see section 4.. 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 *15 time-scales* (section 5.)

For the sake of simplicity in the calculation, we introduce a parameter $\gamma_{i\in\{1,2\}}$ that represents the normalized investment cost of each storage technology (Eq.(1)). We refer to the cost of electricity production per unit of energy produced by γ_3

[†] Batteries 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.

[‡] Electrolyzer life-time is a continuous use lime-time, while other life-times are calendar.

[**] Script for the wavelet decomposition is available on GitHub: `https://github.com/ArthurClerjon/wavelet_decomposition`

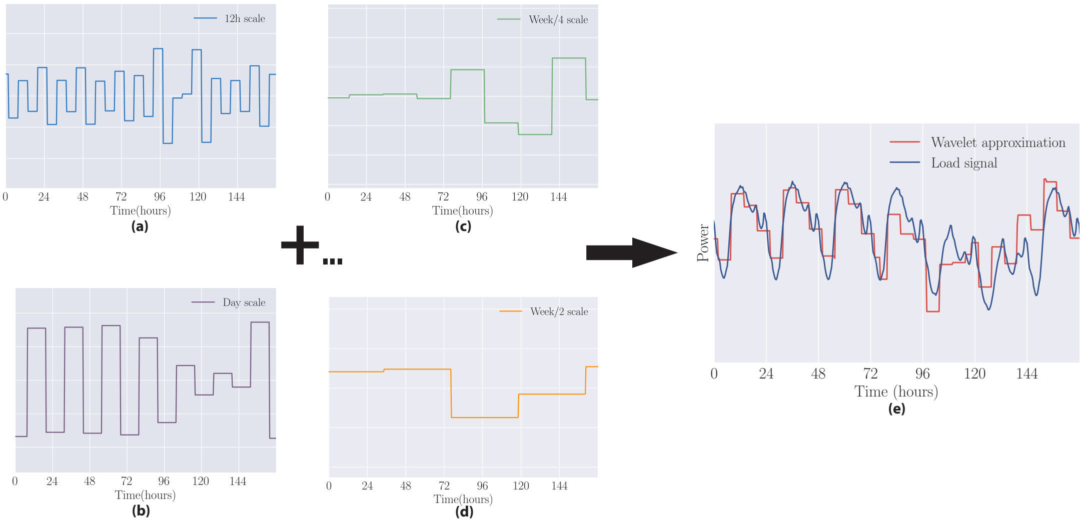


Figure 1: Sketch of the wavelet decomposition. Wavelet signals of time scale ΔT= 12 hours (a), 1 day (b), week/4 (c) and week/2 are summed and placed on top of the original signal (e). Shorter time scales are missing here to show an imperfect approximation.

$$\gamma_i = \frac{\text{Investment cost}}{\underbrace{T_{life}}_{\text{years}}} \tag{1}$$

However, energy storage devices could be both size by their energy and power capacity. To account for it, we respectively refer to the normalized investment as γ_E and γ_P.
Regarding electricity generation systems, we used

$$\gamma_3 = 60\,€/MWh_{produced} \tag{2}$$

See section 2.2. for more details.

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.

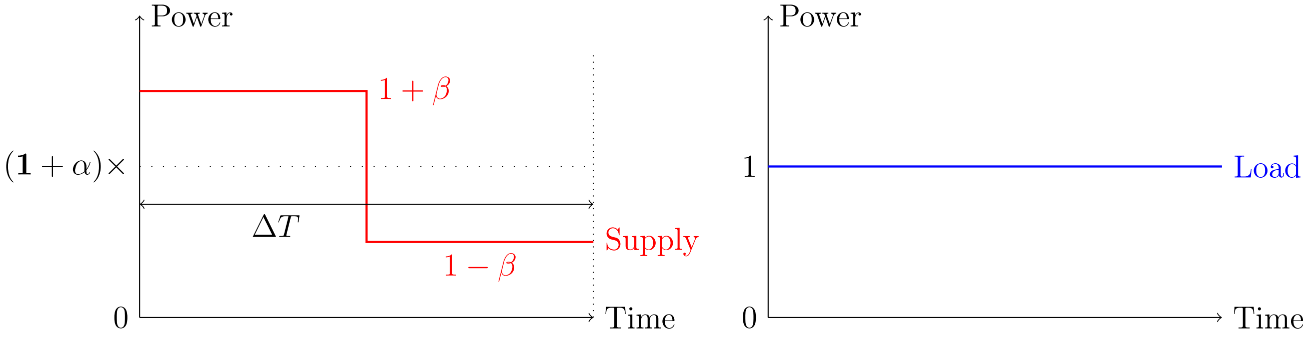


Figure 2: Input signals of the simulation with a single characteristic time-scale.

The energy model includes two electricity storage. We refer to their normalized investment costs as γ_1 and γ_2.

$$Cost_{storage,i} = \gamma_i P_i \frac{\Delta T}{2} \tag{3}$$

P_i is the discharge power. Regarding the electricity generation cost:

$$Cost_{production} = \alpha\gamma_3\overline{\mathbf{P}} \tag{4}$$

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

The Objective Function can be written therefore such that

$$Cost = \gamma_1 P_1 \frac{\Delta T}{2} + \gamma_2 P_2 \frac{\Delta T}{2} + \alpha\gamma_3\ \overline{\mathbf{P}} \tag{5}$$

For real storage objects, investment cost can be both sized by an energy and a power. In the case of power-to-gas for instance, the hydrogen storage sizes the device in energy, the electrolyser and the fuel cell in power. In such cases, γ_i has to be replaced such that

$$\gamma_i \rightarrow \gamma_{i,E} + \frac{2\gamma_{i,P}}{\Delta T} \tag{6}$$

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

Storage characteristics and γ_i are listed in Tab.1.

3.2. Results and discussion

We calculate a literal analytical expression with the Simplex algorithm. 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, a single storage is used:

$$\text{Storage 2 is used} \iff \gamma_1 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_1} \geq \gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_2} \tag{7}$$

   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 $\beta \rightarrow 0$, over-sizing the production by a factor α and curtailing the excess electricity can be relevant in certain cases, while storing it is preferred in other.

$$\text{Electricity is stored} \iff \begin{cases} \gamma_1 \frac{\Delta T}{2} \leq \gamma_3 \\ \text{or} \\ \gamma_2 \frac{\Delta T}{2} \leq \gamma_3 \end{cases} \tag{8}$$

   In that case, a single storage is used:

$$\text{Storage 2 is used} \iff \frac{1}{\eta_1 + 1}\left(\eta_1\gamma_1 \frac{\Delta T}{2} + \gamma_3\right) \geq \frac{1}{\eta_2 + 1}\left(\eta_2\gamma_2 \frac{\Delta T}{2} + \gamma_3\right) \tag{9}$$

We can extract from Eq.(7) and Eq.(9) valuable comparisons between two storages. In particular, we calculate ΔT_{eq}, the time-scale of charge - discharge from which a storage is more relevant that the other – from the optimization stand-point.

$$\begin{cases} \Delta T_{eq,\beta\to 1} = \dfrac{\gamma_3\left(\dfrac{1}{\eta_2}-\dfrac{1}{\eta_1}\right)+2\left(\gamma_{2,P}-\gamma_{1,P}\right)}{\gamma_{1,E}-\gamma_{2,E}} \\ \Delta T_{eq,\beta\to 0} = \dfrac{2\gamma_3\left[\dfrac{1}{1+\eta_2}-\dfrac{1}{1+\eta_1}\right]+2\left[\gamma_{2,P}\left(\dfrac{\eta_2}{1+\eta_2}\right)-\gamma_{1,P}\left(\dfrac{\eta_1}{1+\eta_1}\right)\right]}{\gamma_{1,E}\left(\dfrac{\eta_1}{1+\eta_1}\right)-\gamma_{2,E}\left(\dfrac{\eta_2}{1+\eta_2}\right)} \end{cases} \tag{10}$$

Eq.(8) shows when over-sizing the energy generation and curtailing excess electricity is more relevant than using electricity storages. We denote this specific time scale by $\Delta T_{\beta\to 0,curt}$.

$$\Delta T_{\beta\to 0,curt} = 2\cdot\frac{\gamma_3-\gamma_P}{\gamma_E} \tag{11}$$

Numerical application of Eq.(10) and Eq.(11): 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-scales[‖].

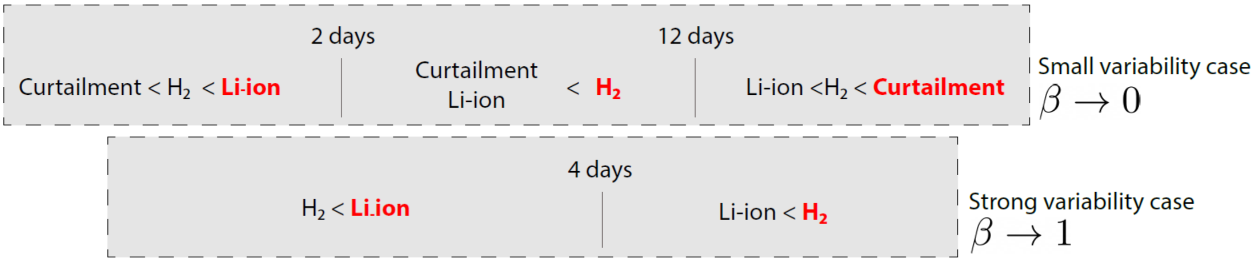


Figure 3: Results calculated for two electricity storages in the framework "*Single time-scale*". It shows which is the most relevant technology to be used, depending of the time-scale usage. Be careful, the cost of the optimal technological solution does not appear. It skyrockets for long time-scale. See reference [2] for more details.

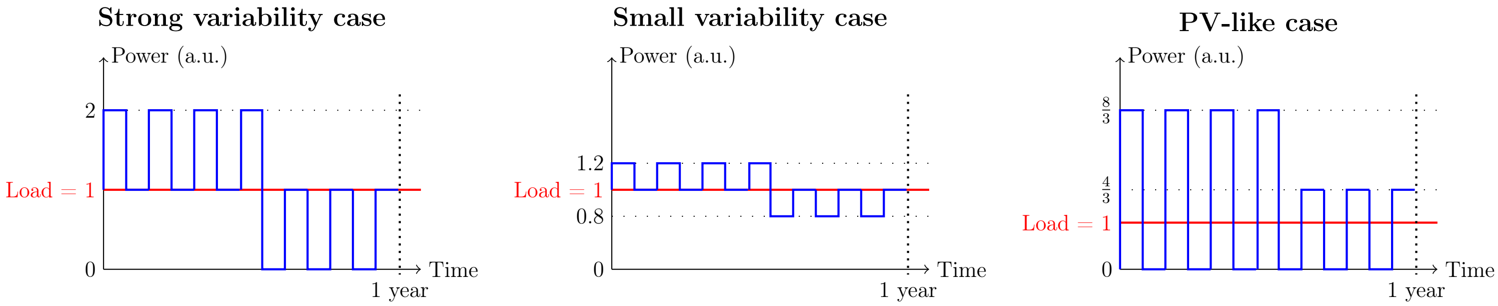
4. Dual time-scale

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 winter*.

[‖] An 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.

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



(a) Input signal with the maximum variability

(b) Input signal with a low variability

(c) Input signal where variability has the PV behaviour

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.

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 100 % to the storage 1. η_2, γ_1 and γ_2 are varying parameters such that

$$\begin{cases} \eta_2 \in [0, 100\%] \\ \dfrac{\gamma_1}{\gamma_3} \in [10^{-1}, 10^{7}] \; (year^{-1}) \\ \dfrac{\gamma_2}{\gamma_3} \in [10^{-1}, 10^{7}] \; (year^{-1}) \end{cases}$$

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 over-sizing factor* of the electricity generation means. We prescribe as input signals *supply* and *load* with equal averages over the year. The supply can by over-sized when compared with this initial average. $E_{discharged,i}$, the total energy discharged by a storage i. It goes along with the size of the storage. And E_{curt}, the total energy curtailed.

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

$$Service = \underbrace{\sum_i \left[E_{discharged,i} - E_{charged,i}\right]}_{\text{storage contribution}\geq 0} + \underbrace{\int_t \left[\alpha P_{supply}(t) - P_{curt}(t)\right] dt}_{\text{oversizing of the production contributution}\geq 0} \qquad (12)$$

Service quantify which devices, from storage 1, 2 or over-sizing, contribute to meet the *Service*.

4.2. Results and discussion

Simulations are made for three intermittent input signals, as depicted on Fig. 2. The result of the *small variability case* is shown Fig. 5. This behaviour is typical of the two other cases.

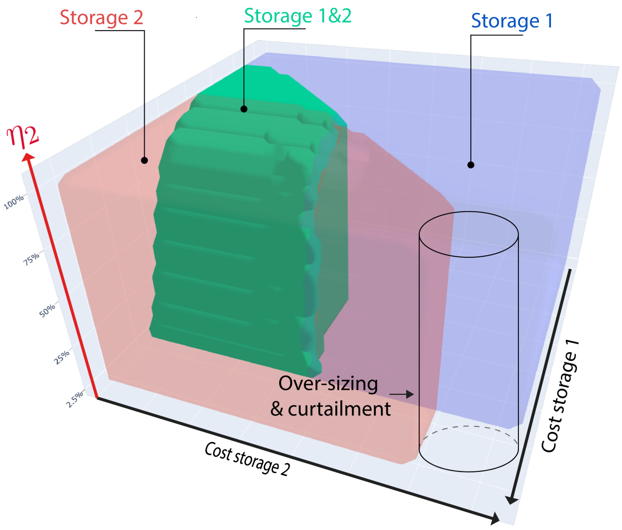
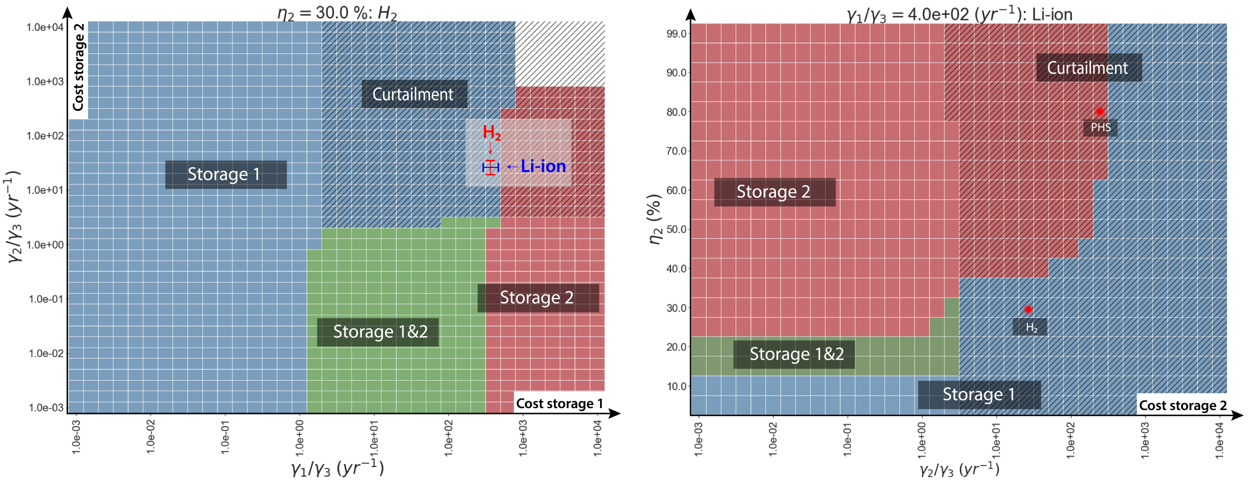


Figure 5: Computation made with the input signal presented on Fig. 4b. The red area corresponds to storage 2, the blue to storage 1. Where the space is green both storages are used in combination. Where there is no color, *Service* is fully provided by the over-sizing.

This figure shows the set of parameters (η_2, γ_1, γ_2) for which both or no storages are used to fulfil the electricity consumption. Obviously, as long as $\eta_2 \neq 100\%$, the optimal solution when $\gamma_2 \geq \gamma_1$ is storage 1.

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

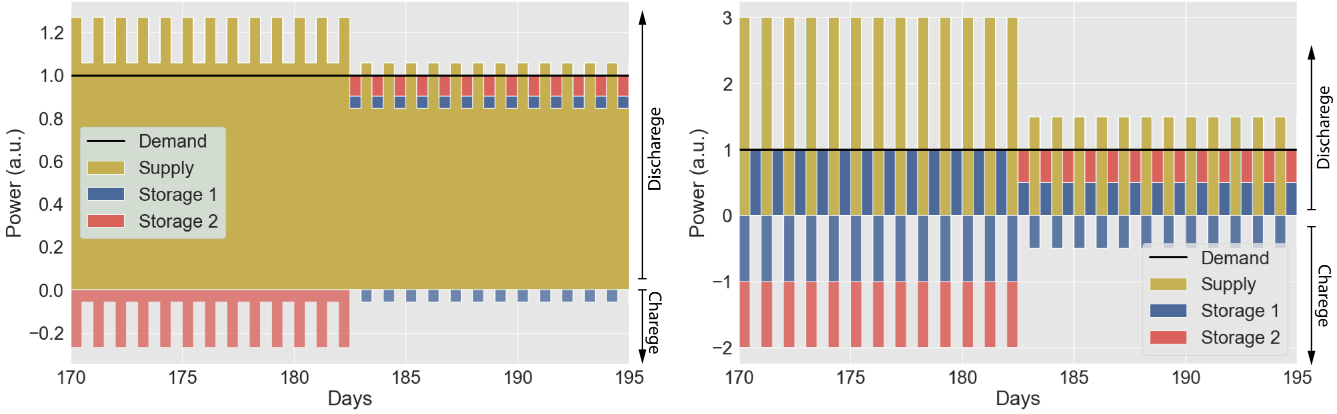
We investigate now further the area where both storages 1 and 2 are used in combination (green area). When both storages are used in conjunction, no electricity is curtailed. In fact, storage 2, when sufficiently low cost, behaves as an improved version of oversizing and curtailing. Among the three different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



(a) Slice with constant $\eta_2 = 30\%$, the efficiency of Power-to-gas-to-Power

(b) Slice with constant ratio $\gamma_1/\gamma_3 = 4 \times 10^2$. It is the average cost ratio of Li-ion batteries

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 over-sizing. This area is denoted by *curtailment*. Energy is also curtailed in the hashed area.



(a) For input signals such as the ones drawn on Fig. 4a and 4b

(b) For the input signal drawn on Fig. 4c

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.

- **Fig. 7a**: Low cost storage 2 is charged during summer days and discharged dunring winter nights. As such, it contributes to the service at both time scales. This is only a behaviour found for input signals of Fig. 4a and 4b.
- **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

5. 15 time-scales: full signal

5.1. Method

Eventually, we use real *load* and *supply* time-series as inputs of the simulation with the yearly French average load factor of 54 GW.

This analysis is carried such that

$$\text{Signals} \xrightarrow{\text{GAMS}} \text{Energy system optimal behaviour} \xrightarrow{\text{WL}} \text{Decomposed results}$$

Over a second phase, optimization output results are decomposed over 15 characteristic time-scales. We study the *Service* repartition, as it is defined in the previous section 4..

This simulation is applied to a 100% PV electricity generation to highlight the features of a strong variability. Results can also be compared with the *PV-like case* described on Fig. 4c.

5.2. Results and discussion

Fig. 8 shows results performed from the residual demand of a 100% PV signal. It includes two electricity storages, *Li-ion batteries* – the expensive and efficienct storage – and power-to-gas through *hydrogen* – the cheap and less efficient one.
The analysis of Fig. 8 shows for which time-scales are used storage 1, 2, and the over-sizing the electricity production – referred to as *Useful oversizing*. We can draw three main conclusions from this analysis. First, the optimal solution combines the use of both storages at short time-scale. Second, the use of Li-ion batteries is only relevant for short time scales. Since it is an expensive storage, it has to perform many cycles in order to provide a substantial *Service* and be made profitable. It is made possible because of its high efficiency. On the contrary, hydrogen is used for longer time-scales , along with the over-sizing of the electricity production. Last, we understand how both storages are being used. Since hydrogen is already installed to handle the long time-scales, it also supports Li-ion at shorter time-scales, in the same way as depicted in Fig. 7b.

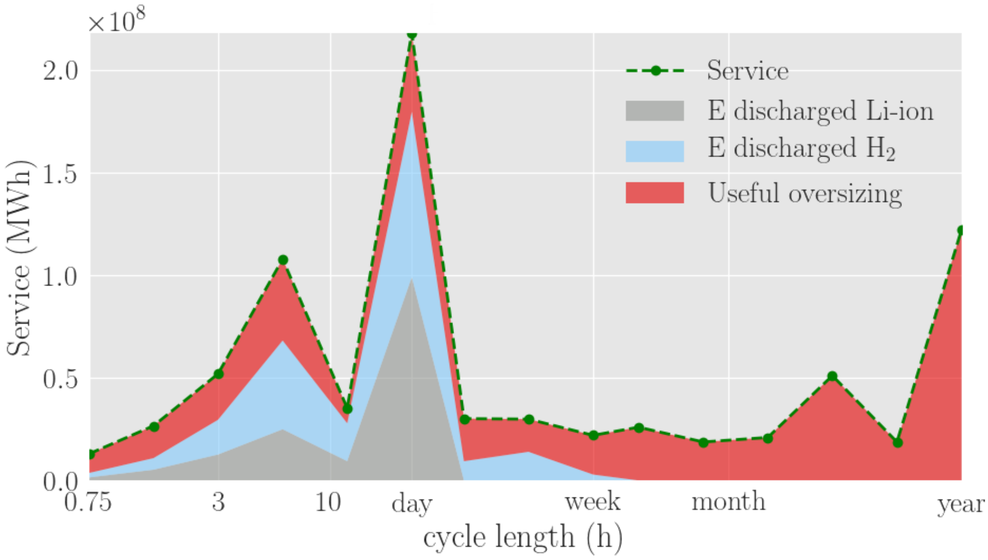


Figure 8: *Service* of the 100% PV residual demand. It is the amount of energy that has to be provided over the year to fill the shortage when *electricity production* $<$ *consumption*. *Service* depends on the time-scale. It could also be seen as the duration of a charge-discharge cycles for electricity storage. The contributions of two storages and the over-sizing of the electricity production is showed here.

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 unpredicted.
- 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 real variable time-series: a one-year of the French photovoltaic electricity production and consumption. We emphasize the fact that the guidelines provided by the first two toy-models are confirmed by this latest most detailed modelling. 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:

- An 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 over-sizing 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.

The numerical examples provided are made with economical costs. However, similar results would be found for indicators such as the *embodied energy* [2], the *Global warming Potential.* As a future work, this study could be extended to the thermal energy vector. 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

Curtailment Oversizing electricity generation means and curtailing excess electricity.

Indexes

T_{life}	Calendar life time
$_{el}$	Electrical
$_{stock}$	Stored electricity
$_{out}$	Output electricity
$_{in}$	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	Over-sizing 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

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