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Renewables and Advanced Storage in Power Systems: The Iberian Case

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Abstract: Storage has many benefits for power systems with a high share of renewable energy. It reduces renewable curtailment, can participate in ancillary services and contributes to system adequacy. However, its business model is far from clear since most of its revenues come from arbitrage in energy markets, and this is usually not enough to recover the investment. Advanced storage can facilitate the profitability of storage and ease the integration of renewables in power systems by reducing costs and allowing an enhanced performance. The profitability requirements of future advanced storage systems (batteries) are assessed in this paper by means of an optimization method and an uncertainty analysis for an optimal Iberian (Spain and Portugal) power system that meets the targets of their National Energy and Climate Plans. Results show that needed storage capacity is only a small part of the demanded energy, but technical advances are required for optimal performance. High prospective storage cost leads to a wind-dominated renewable mix, while low storage cost favours photovoltaics. Arbitrage with storage may cover its investment costs under carbon prices close to the actual Social Cost of Carbon.

Keywords: power system planning; storage; renewable targets

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1. Introduction

Many countries are setting targets for renewable shares to achieve drastic cuts in greenhouse gas emissions. In them, storage will play a crucial role, as widely recognized in scientific literature and official reports such as [1–3].

In particular, the European Union has set a goal of 32% renewable energy share for 2030 [4] in the Clean Energy Package, and higher targets are being discussed. Concerning storage, although not an official target, reference [2] sets a need of 108 GW for storage installed power in the European Union in 2030, while today, the total installed power is approximately 40 GW, mostly coming from hydro pumping power plants.

Storage in power systems includes technologies that have been used for many years, such as pumping hydropower plants or batteries, and others that are in an experimental or precompetitive stage, such as compressed air, flywheels, hydrogen, or supercapacitors. Their applications can be classified into those that can handle large amounts of energy (energy arbitrage, seasonal storage, congestion management, or operational reserves) and others aimed at power quality issues or providing short-term reserves. Each technology has its own niche, although some compete with each other for the same use [5]. In a general way, storage may provide substantial contributions to system adequacy, flexibility, and overall resilience in decarbonized power systems [5,6]. Despite these benefits, the current electricity markets do not foster new storage integration, and often storage meets regulatory barriers [2]. The economic viability and business models for storage are not clear: it is generally agreed that market revenues do not cover investment costs. This is related to the problem of missing money, which also affects generation assets [7,8], particularly with a high renewable energy share [9]. Therefore, technological improvements and lower costs of storage may be of great help to the new decarbonized power systems.

Stakeholders of storage are companies willing to invest in storage facilities, either existing generating companies, consumers, or dedicated companies. European regulation [4] gives a special role to storage facilities, but excludes, with some exceptions, transmission and distribution companies from the property or management of storage facilities. Of course, this might be an obstacle to the optimal sizing and management of system storage.

To perform a prospective study of the future power systems, it is necessary to use power system planning methods. Power system planning with renewable energy targets is a well-established research field, and many references deal with this topic. A short review of those recent references more related to the present work is given below. Interested readers may find a more comprehensive review in [10].

European power system planning is the subject of publications from Schlachtberger et al. (2017) [11], Schlachtberger et al. (2017) [12] and Gerbaulet et al. (2019) [13]. In them, the whole European system with the interconnection capacity between different countries is modelled, and optimal power mixes are found. Storage is addressed in reference [14], where the importance of different storage technologies to achieve greenhouse gas (GHG) targets are underlined. The Spanish system is studied by Martín-Martínez et al. (2017) [15], and the inadequacies of its current regulatory framework are discussed. Regulatory changes are also proposed to promote the needed storage capacity.

Another interesting study is reference [16], where the effects of substituting the French nuclear power fleet for renewables are estimated. Storage is given a cost, and the externalities of renewables in power system operation are considered. Reference [17] presents an agent-based planning model applied to Great Britain, which remarks on the convenience of counting on storage coming from batteries. In publications [18,19], optimal storage capacities for different technologies and their location for a given generation mix are calculated together with sensitivity studies.

Concerning the literature focused on storage, reference [20] is a comprehensive study of the U.S., where long-duration storage compensates for seasonal changes in wind, while short-duration storage (Li-ion batteries) compensates for daily changes in photovoltaics (PV). Another study about long-term storage in the European power system with similar conclusions is presented in [21].

Most of the reviewed papers conclude that arbitrage revenues are not enough to cover investments in storage. Even with participation in reserve or flexibility markets, a capacity mechanism seems necessary for investment recovery. Thus, reference [22] presents a model to set capacity- and energy-based incentives to match revenues and expenses for storage and applies it to a test system. References [17,23] propose additional revenues from capacity mechanisms and flexibility markets to reach the optimal amount of storage. A price cap is proposed in reference [8] in a general analysis of the need for capacity mechanisms. In an interesting work, Fraunholz et al. [24] conducted a deterministic study on the optimal storage and generation connected to several European markets up to 2050 under the assumption of a capacity auction mechanism. An interesting conclusion is that storage does have capacity value; therefore, storage may benefit from existing capacity incentives. Reference [25] also presents conclusions about storage profitability in European markets from past data, whose conclusions are similar.

This paper presents a study on the Iberian power system (Spain and Portugal) for the envisaged renewable energy targets. Investment and operation costs are minimized under different assumptions of storage cost and carbon price. Two storage technologies, batteries, and hydro pumping storage, are considered. The uncertainty in storage costs has been modelled using the two-point estimate method. In this way, the effect of storage cost uncertainty on the optimal deployment of renewables can be easily assessed. This method has not been applied in the examined literature and may have application for other uncertainty studies. The conditions of future storage facilities to arrive at profitability are set and explained. The intended contributions of this paper are the assessment of the uncertainty of storage costs in generation planning with low computational cost, as well as the conditions under which the arbitrage in electricity markets may cover the investment costs of storage. Another contribution is to consider the storage capacity as an optimization variable to check if the envisaged progress of storage technologies would cover power system needs.

The paper is organized as follows. Section 2 presents the storage technologies, particularly those used in the paper. Section 3 gives the mathematical background for the uncertainty/sensitivity study. Section 4 presents the National Energy and Climate Plans for Spain and Portugal, and the data used for the study. Results are given and commented on in Section 5. Section 6 concludes the paper with a summary of the main findings. Two appendices include the optimization problem equations and the preliminary study to select the thermal technologies included in the optimization process.

2. Storage and Its Applications

Storage in power systems comprises technologies with very different properties, costs, and maturity. The main technologies are hydro pumping, batteries (lead-acid, NaS, Li-ion, redox flow, etc.), compressed air, flywheels, supercapacitors, and hydrogen. They may be classified into four groups from the point of view of their possible applications in power systems. Pumped hydro and compressed air, to begin with, may handle large amounts of energy, which allows them to participate in electricity markets for energy and reserve, even with a seasonal timescale, but they cannot be used in small size applications. Hydrogen and Vanadium redox flow batteries combine the possibility of large storage capacity with scalability that allows them to be used by small consumers to optimize energy purchases in combination with distributed generation, such as photovoltaics. Flywheels and supercapacitors are better fitted for short-term applications such as power quality or short-term reserves due to their quick response and short storage capacity. Finally, most of the batteries are in an intermediate place: they can be used by individual consumers or stacked in large units, and can participate in energy and reserve markets, but not on a seasonal scale, and they can also contribute to power system quality. Batteries have experienced in the last year big advances that have dramatically reduced their costs, so they are seen as complementary to intermittent renewables, such as wind or photovoltaics.

A thorough survey of the techno-economic and regulatory status of storage at the international stage is in reference [5], where the deployment and regulatory status in many countries are checked, and an analysis of the main expectations of different technologies is given. Reference [6] makes a useful and extensive survey of different references for a prospective study of storage costs up to 2050. It concludes that batteries are the most competitive short-term storage technology in this time horizon. Among them, lithium-ion technologies seem to be the most efficient for most applications, such as energy balancing, ancillary services (including reserves) and congestion management.

According to reference [6], Lithium-ion batteries may range up to 35 MW, with 5 h of discharge, a life of 3500 cycles and a response time lower than 10 s. Their efficiency is up to 86%, and advanced manufacturing, operation and maintenance cost reductions may reach 60% by 2030.

Applications of the different storage technologies for different sectors of the electricity market are detailed in many references [26]. Official reports such as [1,2] provide a general survey and a prospective view of storage needs and deployment. Reference [2] centres on the contribution of storage to the security of supply, describes the European state of deployment of storage and its potential and provides a set of recommendations to overcome the detected barriers, such as the lack of a viable business case for storage. Notably, seasonal storage does not seem to be a pressing need in the European Union until 2040, according to the study [9]. The need for storage for energy transition is also underlined in reference [27], among other issues, such as the proper way to incentivise renewables and/or the role of demand response. The interaction between storage, renewable energy curtailment and system flexibility is studied in reference [28].

Forecasts for storage advance indicate higher performance and lower costs. For the Li-ion batteries, the most promising technology [6], the investment costs reduce to 23% in 2030 and to 14% in 2050 with respect to the 2015 values. This is the main component of the Levelized Cost of Storage (LCOS), and this reduction leads to a decrease in LCOS from 250 USD/MWh in 2015 to 190–150 USD/MWh [6]. Comments about the need for energy capacity will be made later in this study when discussing the results of the optimization problem.

In our study, we focus on the use of storage for energy balancing, setting aside its participation in ancillary services and contributions to grid services, power quality and reliability, which may also become a source of revenue. However, studies on those contributions require methodologies different from the one used in this paper.

3. Power System Planning under Uncertainty:the Point Estimate Method

3.1. Optimization Problem and Basic Assumptions

To obtain the optimal generation mix of the Iberian power system, an optimization problem has been solved under different assumptions with the following features:

- It obtains the optimal installed power per considered technology and their hourly production for a year. The optimization is made "from scratch", so the current generation mix is not considered a boundary condition.
- No grid constraints are considered. This is a gross simplification, but transmission planning is often performed as a separate task from the generation scenarios previously obtained in a generation planning problem, as in the TYNDP study by ENTSO-E [29].
- These optimized technologies are combined cycle gas turbines (CCGTs), open-cycle gas turbines (OCGTs), onshore wind, solar photovoltaics (PVs) and storage. The thermal technologies were selected after a previous analysis of their screening curves (see Appendix B).
- The operation of existing hydro plants and hydro pumping storage is optimized in a simplified way (single reservoir and operational constraints to in some way reproduce the management of the hydro system).
- The installed power (MW) and the storage capacity (MWh) are included as optimization variables. The considered costs are those of Li-ion batteries. The reason for this choice is that this is the most promising and economical technology for most applications, according to [6]. New pumping hydro facilities must also consider the available places to build them and environmental issues, so the results obtained by an optimization problem would not be realistic.

The mathematical formulation of this problem can be found in [30], and it is repeated in Appendix A.

3.2. Uncertainty Assessment Method

Planning studies face the problem of uncertainty regarding assumptions and parameters. Additionally, the high computational requirements make it difficult to apply usual probabilistic techniques such as Monte Carlo sampling.

However, there are methods that, with a moderate increase in computational time, lead to an assessment of the uncertainty of expected results. Point estimate analysis is a method to obtain the moments of an output variable z from those of an input variable x, where $z = h(x)$, and has been applied to probabilistic power flow (a few basic references are [31,32]). The method may be briefly described as follows. It must be remarked that the method described here is the two-point estimate method, which is the most used method in power system analysis. Other variants might be more convenient for other applications.

Let $z = h(x)$, where x is a random variable, with mean η_x and standard deviation σ_x. Then, the mean value of z, η_z, can be approximated by:

$$E[z] = \eta_z \approx p_1 h(x_1) + p_2 h(x_2) \tag{1}$$

and the second-order moment by the formula:

$$E\left[z^2\right] = m_{z,2} \approx p_1 h^2(x_1) + p_2 h^2(x_2) \tag{2}$$

where x_1 and x_2 are defined in Equation (4). The variance in the random variable z, σ_z^2, is the second order central moment, $\mu_{z,2}$, which can be obtained as:

$$\sigma_z^2 = \mu_{z,2} = m_{z,2} - m_{z,1}^2 \tag{3}$$

where $m_{z,1}$ is the mean value of z and $m_{z,1} = \eta_z$. Parameters p_1 and p_2 are weight coefficients, where $p_1 + p_2 = 1$ and:

$$x_j = \eta_x + \xi_j \sigma_j \qquad j = 1,\ 2 \tag{4}$$

The parameters p_1, p_2, ξ_1 and ξ_2 can be obtained by solving the following set of equations:

$$p_1 + p_2 = 1 \tag{5}$$

$$p_1 \xi_1 + p_2 \xi_2 = 0 \tag{6}$$

$$p_1 \xi_1^2 + p_2 \xi_2^2 = 1 \tag{7}$$

$$p_1 \xi_1^3 + p_2 \xi_2^3 = \lambda_{x,3} \tag{8}$$

where $\lambda_{x,3} = \frac{\mu_{x,3}}{\sigma_x^3}$ and $\mu_{x,3}$ is the third-order central moment of the variable x.

The solution of this system is:

$$\xi_j = \frac{\lambda_{x,3}}{2} + (-1)^{3-j}\sqrt{1 + \left(\frac{\lambda_{x,3}}{2}\right)^2} \tag{9}$$

$$p_j = (-1)^j \frac{\xi_{3-j}}{\zeta} \tag{10}$$

$$\zeta = \xi_1 - \xi_2 = 2\sqrt{1 + \left(\frac{\lambda_{x,3}}{2}\right)^2} \tag{11}$$

for j =1, 2.

The method can be generalized to functions of several variables. Since the method is used here only for one variable, the interested reader may consult the provided bibliography.

4. Study Case: The Iberian System in 2030 According to the National Energy and Climate Plans (NECPs)

4.1. Consumption and Cost Data

Following the request of the European Commission within the Clean Energy for All Europeans package (see [4]), all members of the EU have produced their 10-year National Energy and Climate Plan (NECP) for 2030. Spain [33] and Portugal [34] submitted their plans, with ambitious objectives of 42% and 47%, respectively, of the final energy consumption coming from renewable energy. Table 1 shows the main components of the generation mix in 2019 (2019 has been chosen due to the reduced demand in 2020), with data taken from [35] and the future generation mix in 2030 forecasted by these plans. In the table, combustion fuels for 2019 include coal plants that will be closed by 2030. It is planned that nuclear plants will finish their operation in 2035. The Iberian Peninsula has a large installed pumping hydro capacity, and this capacity will be increased in the next years by converting hydro plants in the same basin into pumping plants by exchanging between upstream and downstream reservoirs. In addition to the National Plan, the Spanish government has published a strategy to facilitate the integration of storage into the power system [36].

Table 1. Generation mix in the Iberian Peninsula - Data from References [33–35].

<table>
<tr><th rowspan="3">Type</th><th colspan="4">2019</th><th colspan="4">2030 (According to the NECP)</th></tr>
<tr><th colspan="2">Spain</th><th colspan="2">Portugal</th><th colspan="2">Spain</th><th colspan="2">Portugal</th></tr>
<tr><th>Installed Capacity (GW)</th><th>Gross Generation (TWh)</th><th>Installed Capacity (GW)</th><th>Gross Generation (TWh)</th><th>Installed Capacity (GW)</th><th>Gross Generation (TWh)</th><th>Installed Capacity (GW)</th><th>Gross Generation (TWh)</th></tr>
<tr><td>Combustion fuels</td><td>46.5</td><td>126.2</td><td>8</td><td>34.9</td><td>24.56</td><td>27.61</td><td>3.30</td><td>14.2</td></tr>
<tr><td>Nuclear</td><td>7.1</td><td>58.0</td><td>-</td><td>-</td><td>3.05</td><td>22.03</td><td>-</td><td>-</td></tr>
<tr><td>Hydro (*)</td><td>20.1</td><td rowspan="3">90.7</td><td>7.2</td><td rowspan="3">24.3</td><td>24.14</td><td>32.37</td><td>8.45</td><td rowspan="3">50.7</td></tr>
<tr><td>Wind</td><td>23.1</td><td>5.1</td><td>48.55</td><td>109.46</td><td>9.3</td></tr>
<tr><td>Solar PV</td><td>7.0</td><td>0.6</td><td>38.40</td><td>65.18</td><td>9.0</td></tr>
<tr><td>Batteries</td><td>0</td><td></td><td>0</td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

(*) Including pumping hydro.

The base case patterns used to run the optimization problem utilize the Iberian power system electricity production data for 2017 because it was a very dry year, and this may better reflect future conditions of water stress due to climate change [37]. Data from wind and solar production have been taken to make a normalized production pattern to be scaled according to the final installed power coming from the optimization process. Demand patterns from 2017 have also been scaled to demand forecasted in the NECP for 2030. Hydro inflows have been calculated from the hourly production of hydro plants in both countries and the state of their reservoirs. Data comes from the Transparency Platform of ENTSO-E [35].

The installed renewable power technologies that are not optimized are those planned for 2030. They include the capacity of hydro and pumping plants, run-of-river hydro, concentrated solar power and biomass. The hourly production patterns of these last three technologies were taken from the 2017 data and scaled to the installed power values shown in Table 2. The capacity factor of hydro plants is very low, since 2017 was a very dry year, as already mentioned. Gross demand (including losses) has been considered because this is the energy that must be finally produced and paid for by consumers.

Table 2. Additional technical data - Data from References [33–35].

Technology	Installed Power (MW)	Capacity Factor (%)
Hydro plants	21,650	7.47
Biomass and others	2330	79.76
CPS	7600	30.94
Pumping hydro	10,940	-
Generated energy in 2030:	367.01 TWh	

To give an idea of the approximation of the copper plate approach followed in the paper, it may be mentioned that congestions between Spain and Portugal take place for less than 5% of the yearly hours and that the energy traded in congestion management in 2019 in both countries was 7621 GWh and that the cost of the remedial actions was 0.99 EUR/MWh for an average day-ahead price of 47.7 EUR/MWh (see [38]).

Cost data are taken from references [11,39,40] for 2030. Costs of storage are taken from [6] for Li-ion batteries. Fixed costs are annuitized and include both investment and fixed operation and maintenance (O&M). They represent the money per MW of the installed capacity that must be recovered each year to pay up the investment and fixed O&M costs over the lifetime of the facility with a given discount rate. The chosen discount rate is 7%. Variable costs include a CO_2 price of 35 €/tCO_2, as in the IMF assessment [41] of fossil fuel externalities. Data are shown in Table 3. The economic lifetime of batteries is lower than the predictable technology cycle life, which depends on the number of charging cycles. As will be shown below, the average depth of discharge of the batteries is approximately 20%, and according to [6], this allows for a longer technological life of the battery than the considered economic lifetime.

Table 3. Cost hypothesis. Carbon price equal to 35 €/tCO_2. Data from References [6,11,39,40].

Technology	Fixed Costs (€/MW y)	Variable Costs (€/MWh)	Lifetime (Years)
Combined cycle	84,464	57.22	30
Open cycle	47,234	86.90	30
Onshore wind	136,428	0.010	25
Photovoltaics	76,486	0.010	25
CSP	215,913	0.010	30
Biomass	278,015	28.42	30
Batt. storage (*)	24,720	17,438 (*)	20

(*) Annuitized fixed costs for MWh capacity in battery storage.

The optimization problem was run for a renewable share of 80% of the total generation. Following the guidelines of the Spanish TSO, a minimum amount of 5.5 GW of thermal or hydro plants must always be connected for ancillary services and security reasons. A ramp constraint of 40% of the installed power for the combined cycle and 80% for the open-cycle plants was considered. Even if a combined cycle plant can give its full power in 1 h [40], it is not possible to switch on more than a given number of plants at a given time. This ramp is consistent with actual practice on the Iberian Peninsula.

4.2. Sensitivity to Uncertainty of Storage Costs. Application of the Power Estimate Method

The standard deviation of investment costs of the installed power of Li-ion batteries in 2030 is estimated as 59% of the mean value, while for capacity, it is 61% of the mean value [6]. In our study, 60% was taken for both parameters. Both random variables have been assumed to be Gaussian, so their skewness is zero. Under these conditions, the parameters defined in Section 3.2 take the following values:

$$p_1 = p_2 = \frac{1}{2} \qquad \xi_1 = \xi_2 = 1 \tag{12}$$

$$x_1 = \eta_x + \sigma \qquad x_2 = \eta_x - \sigma \tag{13}$$

Then, the first- and second-order moments can be obtained as:

$$E[z] = \eta_z = \frac{1}{2}h(x_1) + \frac{1}{2}h(x_2) \; E\left[z^2\right] = m_{z,2} = \frac{1}{2}h^2(x_1) + \frac{1}{2}h^2(x_2) \tag{14}$$

The standard deviation of the output variable is found as $\sigma_z = \sqrt{m_{z,2} - \eta_z^2}$, where x is the cost of storage, and the output variables are the installed power and capacity factors of the optimized variables.

In summary, simulations are run for the following cases:

1. The base case, with the cost parameters shown in Table 3.
2. A second case, where the costs of storage have been increased by a standard deviation.
3. A third case, where the costs of storage have been decreased by a standard deviation.

Using the point estimate method, the average value and standard deviations of the output variables are found.

An outline of the whole process is given in Figure 1.

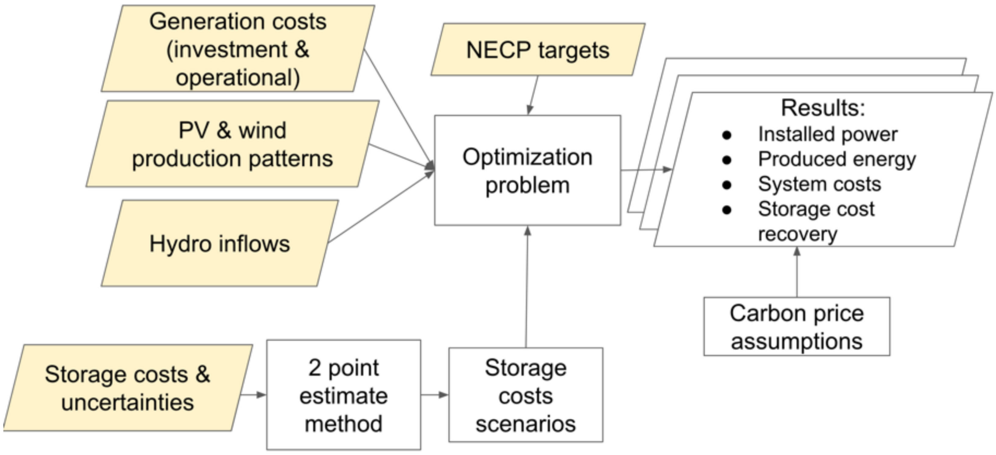

Figure 1. Outline of the followed method.

5. Results and Discussion:Sensitivity Analysis

5.1. Base Case and Sensitivity to the Uncertainty of the Storage Costs

The solution of the problem for the optimization variables is shown in Figures 2 and 3, and the numerical values are given in Table 4. The capacity factor (CapF) is the ratio between the average delivered power and the installed power.

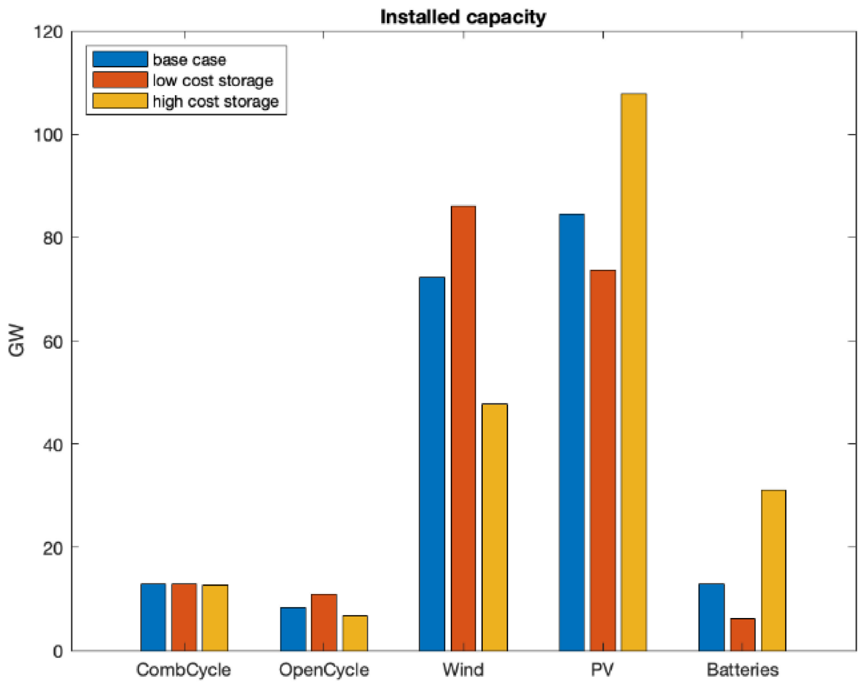

Figure 2. Optimization results. Installed capacities.

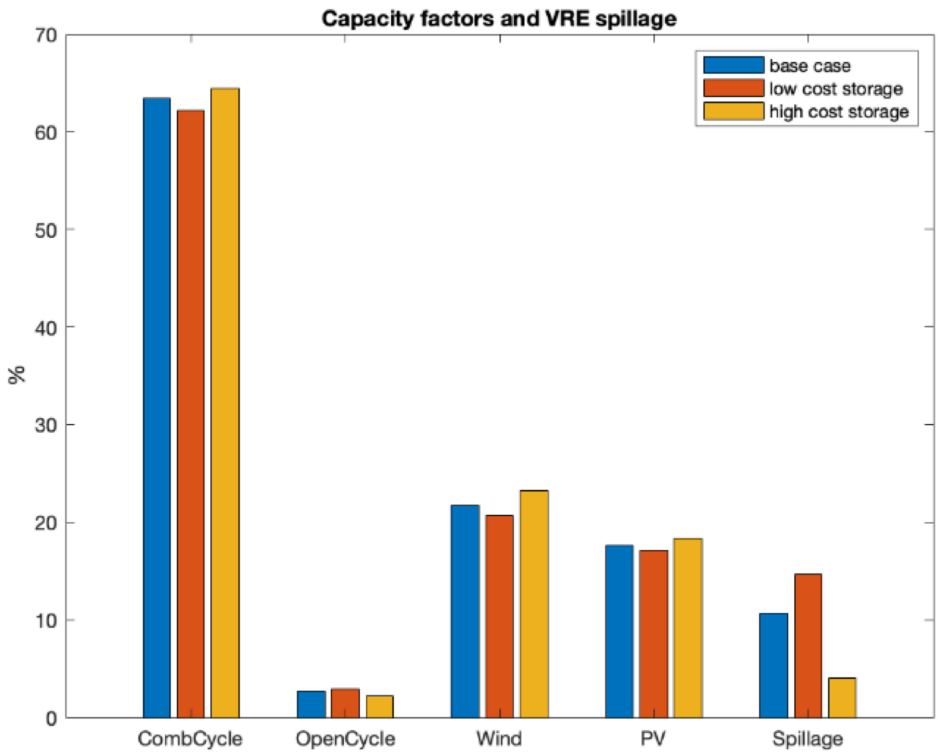

Figure 3. Optimization results. Capacity factors and VRE spillage.

Table 4. Optimization results. Total generation: 367.01 TWh.

	Base Case		$x_1 = \eta + \sigma$		$x_2 = \eta - \sigma$	
	P (GW)	**CapF (%)**	**P (GW)**	**CapF (%)**	**P (GW)**	**CapF (%)**
Comb. cycle	12.86	63.39	12.96	62.17	12.78	64.41
Open cycle	8.25	2.73	11.01	2.94	6.73	2.15
Wind	72.34	21.69	86.08	20.68	47.74	23.26
PVs	84.58	17.62	73.71	17.13	107.76	18.37
Storage (batteries)	12.95	-	6.25	-	31.18	-
Storage hours	6.74	-	4.99	-	7.14	-
Storage capacity (GWh)	87.28	-	31.19	-	222.63	-
Storage as % of demand	0.0502		0.0359		0.0848	
Spillage VRE (%)	10.7		14.69		4.07	

Compared with the generation mix of the Iberian countries in Table 1, the installed power of the combined cycle plants is much lower in the simulation because the national plants maintain the existing capacity. The capacity factors of wind and PVs are higher in the national plans than in actual past years, and nuclear plants are still present (the phaseout in Spain will end in 2035). In addition, batteries should be already installed in 2030, so costs before that date should have been used in the simulation. This inconsistency is considered in the sensitivity study, where higher storage costs have been considered. In any case, the constraint of keeping the study as close as possible to the present power system moves the generation mix of the national plans away from that obtained from scratch. Comparisons to other simulations studies such as [12–15] are difficult because the assumptions, considered technologies, and geographical scope are widely different. All of them, however, remark the importance of storage in an intermittent renewable-dominated power system.

Since the aim of the paper is to study the need for advanced storage in the optimal generation mix and its sensitivity to storage costs, the comparison to these studies is just informative.

The estimates of mean values and standard deviations for installed power and capacity factors are shown in Table 5. It must be recalled that for $z = f(x)$, the mean value of the output variables (installed power and capacity factors) is not the output of the mean of the input variable (storage cost), i.e., $\eta_z \neq z = f(\eta_x)$. The energy produced by all technologies is different in each case because of different storage capacities and subsequent losses.

Table 5. Sensitivity analysis with the considered uncertainty.

	Mean Value		σ (% of Mean Value)	
	P (GW)	**CapF (%)**	**P**	**CapF**
Comb. cycle	12.87	63.29	0.70	1.77
Open cycle	8.87	2.55	24.13	15.52
Wind	66.91	21.97	28.65	5.87
PVs	90.74	17.75	18.76	3.49
Storage (batteries)	18.72	-	66.60	-
Storage (hours)	6.07	-	17.72	-
Storage capacity (GWh)	113.51	-	98.04	-
Spillage wind + PV (%)	9.38		56.61	

These results lead to the following conclusions:

- As expected from the screening curve analysis (see Appendix B), OC technology is an economical option for the optimal mix, even if its capacity factor is low. The optimal capacity of OC decreases when storage increases because both storage and OC compete in peak shaving of the residual demand.
- Storage reduces the spillage of wind and particularly PVs. Storage is mainly used to compensate for the daily cycle of PVs. When the storage is low, the target of 80% renewables is covered mainly by wind, while more storage leads to more installed PVs.
- The energy capacity of storage is a very small fraction of the total demand (0.08% in the largest case). This point is commented in reference [30], where it is shown that even for a 100% renewable system based on PV and wind (under different assumptions), the needed storage remains low compared to demanded energy. This result agrees with the results of reference [42], which includes a detailed review of many other references. It must be remarked that the actual installed capacity of storage in real systems would likely be higher because of the distributed storage facilities. This would not be an optimal scenario, but to design a regulation that fosters the optimal deployment of storage is challenging.
- The number of hours of storage changes slightly because storage is used for the daily cycling of PVs. The optimal number of storage hours has a mean value of 6.26, which is over the limit of the technological possibilities of the Li-ion family. This means that to use massive Li-ion storage in the optimized power system, further technological enhancements should be expected. The scenario with high reduction costs for storage would require an even higher increase in capacity to reach the optimal point. For the base case, the average depth of discharge is approximately 20% on a daily cycle basis,

which means that the technical life of the battery is longer than the chosen economic lifetime, according to [6].

- The large uncertainty in the storage prices of 2030 does not produce large changes in the installed power or capacity factor of the combined cycle technology.

5.2. Revenues and Costs of Storage:Sensitivity Study

The total costs of the supplied energy are shown in Table 6, including the fixed costs (investment and fixed O&M) and variable costs (fuel and CO_2). Costs are shown for the base and extreme cases, as well as their mean values and standard deviations. An increase of 15% in the capacity of the thermal plants to account for their reliability and reserves was considered.

Table 6. Cost of energy and storage.

	Base	x_1	x_2	**Mean**	σ (*)
Energy cost (€/MWh)	72.41	74.95	70.24	72.60	3.24
Average marginal price (€/MWh)	35.53	34.56	37.33	35.95	3.85
Storage cost (M€/year)	1600.00	970.44	1617.80	1294.12	25.01
Storage revenues (M€/year)	751.84	294.89	1561.10	928.00	68.22

(*) % of mean value. NOTE: x_1 and x_2 mean the high and low storage cost assumptions, respectively.

It is interesting to compare the revenues of storage from arbitrage with the investment costs. To do this, it is necessary to calculate the price of energy in an auction as in the current European day-ahead market, without the requirement for a minimal 5.5 GW of dispatchable energy. This limit will be applied in a subsequent process that will keep the hourly prices set by the daily auction, according to the Spanish market rules.

To this end, a simulation was performed, keeping the installed power obtained in the optimization process and optimizing the operation of this generation mix without the constraint of the minimal dispatchable power. The cost of the marginal technology reproduces the pricing mechanism under the conditions of perfect competition and gives a better approximation of the revenues of storage, namely, the marginal prices that would be used to buy and sell energy. The price distribution is shown in Table 7. It can be seen that the largest change is the number of hours when the open cycle sets the prices since this technology competes with storage during peak hours. Interestingly, the percentage of the demand covered by thermal technologies (in the last row of Table 6) is lower than the target of 20%.

Table 7. Market results.

	Base	x_1	x_2	**Mean**	σ (*)
No. hours OC sets price	264	473	218	352	41.68
No. hours CC sets price	5004	4549	5295	4566	4.97
No. hours zero prices	3492	3738	3247	3843	2.09
% of thermal generation	15.83	15.15	16.89	16.0	5.43

(*) % of mean value. NOTE: x_1 and x_2 mean the high and low storage cost assumptions, respectively.

Table 6 gives the costs for the different cases. It may be seen that the market prices do not cover the energy costs. The "missing money" problem (see Appendix B), especially when renewable technologies set a zero price in the market, is more remarkable than under nowaday conditions. Furthermore, the costs of storage cannot be recovered by arbitrage either, even in the case of a low storage cost (case x_2). This reinforces the need for capacity mechanisms for storage if all the advantages of this technology are to be used.

5.3. Effects of the CO_2 Price: Sensitivity Study

Previous results have been obtained for a CO_2 price of 35 €/tCO_2. The optimization program was run with higher CO_2 prices, namely, 50 €/tCO_2, 100 €/tCO_2, and 185 €/tCO_2. The first is close to the average carbon price in the European market in the first half of 2021. The second value is approximate to the average value of the Social Cost of Carbon for 2030 in [43]. The last value is just beyond the turning point when storage begins to be profitable from arbitrage, and it is in the upper limit of the estimates for the Social Cost of Carbon in [43]. The results of these simulations are summarized in Table 8. In all cases, the generation mix and the optimal storage capacity and power change only marginally. Thus, storage revenues increase with the increasing price of CO_2.

Table 8. Cost of energy and storage for different CO_2 prices.

	Base	**50 €/MWh**	**100 €/MWh**	**185 €/MWh**
Energy cost (€/MWh)	72.41	76.40	80.11	86.41
Average marginal price (€/MWh)	35.53	38.67	47.51	60.32
Storage cost (M€)	1600.00	1598.70	1598.10	1597.8
Storage revenues (M€)	751.84	822.05	1082.80	1629.7

6. Conclusions

This paper has presented a simulation study that yields the optimal generation mix in the Iberian Peninsula (Spain and Portugal) to comply with the renewables targets of their National Energy and Climate Plans, under certain assumptions. The study is the result of a high-dimensional optimization problem. Sensibility studies have been run to assess how storage cost uncertainties and CO2 prices affect the generation mix. This uncertainty analysis has been run using a mathematical method aimed at reducing the computational burden. The main findings of this study are summarized below.

Storage is a need for a generation mix with a high share of renewables, and the optimal storage capacity is a small part of the consumed energy. Storage capacity is used mostly to compensate for the daily cycle of PVs. This is shown by the optimal capacity of the storage, which is slightly above 6 h for the average forecasted cost for storage.

This optimal storage capacity is close to the technical possibilities of Li-ion batteries, and further technological advances would be needed to increase the capacity of these batteries to meet the requirements of a renewable-based power system.

The optimal renewable mix depends on storage costs—more expensive storage leads to more wind power, whereas less expensive storage means more PVs in the mix. The considered uncertainty of the future costs of storage, with a standard deviation of 60% of the average estimated cost, leads to an uncertainty with a standard deviation of 28.65% of the installed power for the wind, and 18.76% of the PV.

Renewable generation competes with storage. To achieve the renewable target, more renewable power with a lower capacity factor must be installed if storage is expensive, and the opposite must happen if storage is inexpensive. Thus, the spillage of intermittent renewables with more installed storage capacity is around 4% of the production, whereas with less storage is almost 15% of the production.

Storage costs have a small effect on the amount of installed power and the capacity factor of base thermal generation, but they have a noteworthy effect on the installed power of peakers, wind, and PVs. For the assumption of low storage cost, the reduction in installed power of open-cycle plants is 19% over the base case, and for the high-cost assumption, there is an increase of 33%. The impact on the capacity factors of renewable technologies is lower in relative terms, although it leads to a relatively high spillage of renewable production, as already mentioned.

With high carbon prices, close to the upper limits of the Social Cost of Carbon for 2017 (185 €/tCO_2 in this study), arbitrage revenues might recover the investment costs of battery storage. This conclusion holds, provided that thermal plants are present in the generation mix and set the marginal price. With lower carbon prices, a capacity mechanism is needed for the cost recovery of storage investments, although the participation of storage in reserve and flexibility markets may alleviate this need.

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Abbreviations

The meaning of the different symbols and variables are as follows:

Superscripts	
CC	combined cycle
OC	open cycle
W	onshore wind
PV	photovoltaics
S	battery storage
H	hydro
P	pumping storage
Constants and Indices	
t	index of hourly time steps, running from 1 to 8760.
FC_n	fixed costs of technology n (€/MW-year)
VC_n	variable costs of technology n (€/MWh)
P_n	installed power of technology n (fixed) (MW)
D_{TOT}	total yearly demand (MWh)
P_{DISP}	minimum dispatchable power (MW)
x_{REN}	ratio of energy provided by renewables (p.u.)
D_t^*	hourly average residual demand in time step t (MW)
k_{grad}^n	allowed gradient of technology n (p.u.)
ΔH^{max}	allowed gradient of hydro production (p.u.)
ε^n	maximum production of wind and PVs (p.u.)
$\eta^{(+/-)}$	efficiency from/to storage (p.u.)
η^{H+}	efficiency of hydro plants (p.u.)
$\eta^{(P+/-)}$	efficiency from/to pumping storage (p.u.)
E_t^{in}	average power inflow to hydro plants in t (MW)
Variables	
P_n	installed capacity of technology n (MW)

E^S	capacity of battery storage (MWh)
P_t^n	hourly average power from technology n in t (MW)
$P_t^{(+/-)}$	hourly average power from/to storage in t (MW)
$P_t^{(P+/-)}$	id. of pumping storage in t (MW)
$P_t^{(H+)}$	average hourly production of hydro plants in t (MW)
E_t^S	stored energy in batteries in hour t (MWh)
E_t^{PS}	stored energy in pumping plants in hour t (MWh)
E_t^{HS}	stored energy in hydro plants in hour t (MWh)
Y	set of optimization variables

Appendix A. Optimization Model

The formulation of the optimization problem of the generation mix is written below. These equations are taken from [30].

Objective function

$$\begin{aligned} min_Y\ & FC^{CC}P^{CC} + VC^{CC}\sum_t P_t^{CC} + FC^{OC}P^{OC} + VC^{OC}\sum_t P_t^{OC} + FC^W P^W + VC^W \sum_t P_t^W \\ & + FC^{PV}P^{PV} + VC^{PV}\ \sum_t P_t^{PV} + FC_P^S P^S + FC_P^S P^S + FC_E^S E^S \end{aligned} \tag{A1}$$

subject to

$$P_t^{CC} + P_t^{OC} + P_t^W + P_t^{PV} + P_t^H + P_t^+ - P_t^- + P_t^{P+} - P_t^{P-} = D_t^* \quad \forall t \tag{A2}$$

$$E_t^S = E_{t-1}^S - \frac{1}{\eta^+}P_t^+ + \eta^- P_t^- \tag{A3}$$

$$E_t^{PS} = E_{t-1}^{PS} - \frac{1}{\eta^{P+}}P_t^{P+} + \eta^{P-}P_t^{P-} \tag{A4}$$

$$E_t^{HS} = E_{t-1}^{HS} - \frac{1}{\eta^{H+}}P_t^{H+} + E_t^{in} \tag{A5}$$

$$\sum_t \left(P_t^{CC} + P_t^{OC}\right) \leq (1 - x_{ren})D_{TOT} \tag{A6}$$

$$P_t^{CC} + P_t^{OC} + P_t^{H+} \geq P_{DISP} \quad \forall t \tag{A7}$$

$$P_t^{CC} - P_{t-1}^{CC} \leq k_{grad}^{CC}P^{CC}\ ;\ P_{t-1}^{CC} - P_t^{CC} \leq k_{grad}^{CC}P^{CC} \quad \forall t \tag{A8}$$

$$P_t^{OC} - P_{t-1}^{OC} \leq k_{grad}^{OC}P^{OC}\ ;\ P_{t-1}^{OC} - P_t^{OC} \leq k_{grad}^{OC}P^{OC} \quad \forall t \tag{A9}$$

$$P_t^H - P_{t-1}^H \leq \Delta H^{max}\ ;\ P_{t-1}^{CC} - P_t^{CC} \leq \Delta H^{max} \quad \forall t \tag{A10}$$

$$P_t^{CC} \leq P^{CC}\ ;\quad P_t^{OC} \leq P^{OC} \quad \forall t \tag{A11}$$

$$P_t^W \leq \varepsilon^W P^W\ ;\quad P_t^{PV} \leq \varepsilon^{PV}P^{PV} \quad \forall t \tag{A12}$$

$$P_t^{P+} \leq P^P\ ;\quad P_t^{P-} \leq P^P\ ;\ P_t^{H+} \leq P^H \quad \forall t \tag{A13}$$

$$P_t^+ \leq P^S\ ;\quad P_t^- \leq P^S \quad \forall t \tag{A14}$$

$$E_{min}^S \leq E_t^S \leq E_{max}^S\ ;\ E_{min}^{PS} \leq E_t^{PS} \leq E_{max}^{PS}\ ;\ E_{min}^{HS} \leq E_t^{HS} \leq E_{max}^{HS} \quad \forall t \tag{A15}$$

Equation (A1) models the total costs, including investment, fuel and O&M. Equation (A2) sets the equality of generation and demand. The residual demand has been calculated as the difference between consumed and the non-optimized renewable generation. Equations (A3)–(A5) models the stored energy balance from the different storage systems considered, namely batteries, hydro plants and hydro pumping plants. Equations (A6) and (A7) sets the renewable targets and the Spanish System Operator constraint of minimum dispatatchable power. Equations (A8)–(A10) model the ramp limits of considered technologies, hydro plants included because of the impossibility of connecting a given number of hydro plants at the same time. Equations (11)–(15) sets the limits for the optimization variables. Wind and PV are also limited according to the existing resource at a given moment. Their production, however, can be spilled.

The problem was programmed in MATLAB® and solved using the function linprog. The problem has 105,126 variables, 131,402 inequality constraints and 35,040 equality constraints. The average running time for each simulation is 962.745 s in a computer with 16 GB RAM and a 1.3 GHz processor.

Appendix B. Screening Curves:Technology Choice and Missing Money

Appendix B.1. Economical Technologies

The theory of the screening curves for power system planning is summarized here. It may be conveniently found in [44].

Costs of a given technology or plant may be written as:

$$ARR = FC + \alpha VC \ (€/\mathrm{MWh}) \tag{A16}$$

where ARR is the annual revenue requirement per kW; FC are the annuitized fixed costs (investment and fixed O&M) divided by the hours in the year; VC are the variable costs, including fuel and CO_2 costs; and α is the fraction of the year that a given technology is used at full or partial capacity. If the analysis is made for base and peak technologies, the crossing of the screening curves of both technologies gives the optimal number of hours that these technologies will be working, i.e., the optimal α. The formula that gives this is:

$$\alpha_{opt} = \frac{FC_{base} - FC_{peak}}{VC_{peak} - VC_{base}} \tag{A17}$$

The installed power of this technology depends on the thermal load-duration curve so that the plants are used according to this result. If $\alpha_{opt} > 1$, then the only technology present will be the peak technology. This method can be used for several technologies and will yield the optimal generation mix for a given thermal demand.

According to data from [38], the fixed and variable costs of the most common thermal technologies are (Table A1):

Table A1. Fixed and variable costs of thermal technologies. Data from references [38].

Technology	FC (€/MWh)	VC (€/MWh)
Nuclear	66.61	19.3
Lignite	23.41	54.12
Hard coal	22.27	51.89
Gas combined cycle	9.64	57.22
Gas open cycle	6.77	86.9

A discount rate of 7% and 35 €/tCO_2 were considered. From these values, the crossing points of these screening curves are (Table A2):

Table A2. Values of α_{opt} for the thermal technologies.

α_{opt}	Lignite	Hard Coal	Comb. Cycle	Open Cycle
Nuclear	1.24	1.36	1.50	0.89
Lignite	-	1.24	4.44	0.51
Hard coal	-	-	2.37	0.44
Comb. cycle	-	-	-	0.01

Since all results with $\alpha_{opt} < 1$ are unfeasible, these results indicate that the only technologies that should be considered according to this method are the open cycle and combined cycle, with very short use of open cycle technology (α_{opt} = 0.01), value that matches the obtained results in the base study case.

Appendix B.2. Missing Money

Consider that there are N technologies ordered such as:

$$CV_1 > CV_2 > \ldots > CV_N \quad \text{(A18)}$$

For technology n ($1 \leq n \leq N$), the total costs TC_n for a year can be found as:

$$TC_n = FC_n P_n H_y + CV_n E_n \quad \text{(A19)}$$

where P_n is the installed power of the technology, H_y is the number of hours in a year, and E_n is the yearly energy.

Assuming perfect competition conditions, where the marginal technology sets the price and this is the marginal cost, the total revenues of technology n, TR_n, are:

$$TR_n = CV_n E_n + P_n H_y \sum_{j=1}^{n-1} \left(CV_j - CV_{j+1}\right)\alpha_j \quad \text{(A20)}$$

Combining the revenues and cost equations, it can be demonstrated that:

$$TC_n = TR_n + FC_1 P_n H_y \quad \text{(A21)}$$

where $FC_1 P_n H_y$ is the "missing money" of the technology, i.e., the part of the costs that cannot be recovered from the energy sold to the market under perfect competition conditions.

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