



A methodological approach for assessing flexibility and capacity value in renewable-dominated power systems: A Spanish case study in 2030

Sébastien Huclin^{a,b,*}, Andrés Ramos^a, José Pablo Chaves^a, Javier Matanza^a, Mikel González-Eguino^b

^a Institute for Research in Technology (IIT)-ICAI School of Engineering, Universidad Pontificia Comillas, Alberto Aguilera 23, 28015, Madrid, Spain

^b Basque Centre for Climate Change (BC3), Sede Building 1, 1st floor, Scientific Campus, 48940, Leioa, Spain

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ABSTRACT

Maintaining the security of supply is one of the challenges that system operators face. Variability and uncertainty increase due to the penetration of variable renewable energy sources such as solar and wind, while flexible technologies such as traditional thermal units are phased out to reduce emissions. The current methods for assessing power system adequacy are based on historical operations and are generally intended to be applied to thermal-dominated electricity systems. Therefore, it is necessary to improve current adequacy assessment methods since they usually neglect the flexibility of power systems. This paper presents a methodological approach for jointly assessing the adequacy and flexibility of power systems. The methodology's usefulness is demonstrated through its application to the Spanish power system. For the case study, results show that new closed-looped pumped storage hydro technology provides 25% flexibility while contributing to adequacy due to higher installed capacity and round-trip efficiency. Due to shorter storage duration, batteries only contribute to flexibility, supplying 16% of the total operating reserves. Therefore, this study shows that metrics of flexibility and individual contribution to the power system adequacy complement each other and simultaneously enable the scarcities of power systems to be observed.

1. Introduction

As the capacity of variable renewable energy sources (VRESs) increases, power systems will have to cope with more uncertainty and variability to avoid jeopardising the security of supply (SoS) [1]. SoS studies, also called adequacy analysis, determine whether power systems have sufficient capacity to satisfy load demand whilst maintaining the reliability standards (e.g., Loss of Load Expectation, Expected Unserved Energy). Reliability standards have traditionally been based on the historical availability of thermal and hydropower generation units [2]. However, in the context of the transition from fossil fuel-to renewable-dominated power systems with new technologies such as batteries, authors in [3] underline the importance of considering wholesale operational flexibility when assessing the adequacy of power systems. Although there are several tools for analysing the power system flexibility [4], it remains unclear how the contributions of

technologies to the provision of adequacy and flexibility should be assessed simultaneously [5].

In the context of VRES integration, Spain is an interesting real case study for the challenges of assessing the adequacy and operational flexibility since the Spanish National Energy and Climate Plan (NECP) [6] aims for a minimum of 74% of the country's electricity to be produced from renewables by 2030. From 2020 to 2030 the Spanish NECP envisages a significant increase of 70% in installed capacity for solar photovoltaic (Solar PV), 40% for wind, and 64% for Energy Storage Systems (ESSs) — i.e., Pumped Storage Hydro (PSH) and batteries. The future ESS mix in Spain will mainly consist of batteries and new and existing PSHs [6], so the participation of batteries in providing balancing services was included in December 2020 in the operating procedures of the Spanish System Operator (SO) [7]. However, even if ESSs and thermal power plants may provide flexibility in avoiding

Abbreviations: VRES, Variable renewable energy source; SoS, Security of Supply; IRENA, International Renewable Energy Agency; NECP, National Energy and Climate Plan; ESS, Energy Storage System; PSH, Pumped Storage Hydro; SO, System Operator; CLPSH, Closed-Loop Pumped Storage Hydro; OLPSH, Open-Loop Pumped Storage Hydro; EFC, Equivalent Firm Capacity; ELCC, Effective Load Carrying Capability; DFT, Discrete Fourier Transform; SEED, Spanish Electricity and Economic Dispatch; CCGT, Combined Cycle Gas Turbines; TYNDP, Ten-Year Network Development Plan; EFOR, Expected Forced Outage Rate

* Corresponding author at: Institute for Research in Technology (IIT)-ICAI School of Engineering, Universidad Pontificia Comillas, Alberto Aguilera 23, 28015, Madrid, Spain.

E-mail address: shuclin@comillas.edu (S. Huclin).

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VRES curtailments [8], there is currently no remuneration for such services [5].

A transparent, technology-neutral methodology would facilitate the creation of new market mechanisms and reward technologies for the different system services that they provide (e.g., balancing, energy, ramps, capacity). Some services, such as energy or balancing, have long been provided, while others have only recently been proposed, such as the Flexible Ramp Product in the Californian electricity system [9]. Furthermore, although all dispatchable technologies are, a priori, allowed to provide several services, some technologies might not be able to contribute to some services because of their own parameters. Thus, the methodology for assessing flexibility and adequacy contributions should highlight the technology dilemma; which service could be provided most efficiently?

Currently, there is active research on how adequacy assessment methods could consider flexibility aspects in their analysis. Several studies have investigated the shortcomings of existing adequacy metrics. For instance, [10] proposed an adequacy metric for considering ramp shortage and thus integrating flexibility aspects when assessing the power system adequacy. Although they demonstrated the limitations of traditional capacity value metrics in capturing the full potential of flexible resources in a renewable-dominated system, their proposed metric does not capture the flexibility challenges occurring at different timescales. Furthermore, [11] conducted a comprehensive analysis of flexibility metrics, highlighting the need for a more integrated approach. Despite these insightful contributions, a significant knowledge gap still exists in the field. Existing methodologies and tools for analysing flexibility and reliability have primarily been developed separately, without a clear method for their simultaneous integration. While [12,13] have introduced valuable concepts and tools for assessing flexibility and reliability independently, there is a notable absence of a unified method that effectively combines both aspects in the context of renewable-dominated power systems.

This study presents a methodology that permits a quantitative analysis of which technologies are most actively involved in the different aspects of power system flexibility and in maintaining the SoS. The methodology seeks to obtain a quick overview of the services provided by dispatchable technologies for flexibility and adequacy. This article draws on existing methods and tools and organises them to build a new methodological approach and thus respond to the dilemma facing technologies. The review of operation models or tools for flexibility analysis goes beyond the scope of the paper.

This paper makes several contributions:

1. It proposes a new approach to analysing the contributions of individual technologies to the adequacy of renewable-energy-dominated electricity systems with different storage technologies such as Pumped Storage Hydro (Closed- and Open-Loop Pumped Storage Hydro, (CLPSH, and OLPSH, respectively)) and batteries.
2. Based on the new approach, it defines novel measures that capture the behaviour of technologies in providing operational flexibility and adequacy. These behaviours are assessed on different time scales and with regard to several scarcities in power systems that pose a challenge for the integration of VRES.
3. The methodology is tested in a real case study: the Spanish power system for 2030 based on the NECP. Furthermore, to demonstrate its robustness, the methodology is applied to extreme scenarios to provide sensitivity analyses according to critical parameters of the Spanish power system.

The study is organised as follows: Section 2 presents the state of the art of power system adequacy assessment methods and operational flexibility. Section 3 describes the measures and methods proposed. Section 4 details the case study considered and the sensitivity scenarios. The results are provided and analysed in Section 5. Section 6 summarises the main conclusions.

2. State-of-the-art: adequacy assessments and flexibility metrics

This section is subdivided into three subsections. Section 2.1 reviews existing adequacy assessment methods. Section 2.2 exposes critical aspects of power systems due to the integration of VRES, which are not adequately covered by current adequacy assessment methods. Given that these unaddressed aspects are closely linked to the concept of flexibility, Section 2.3 delves into the definition of flexibility and presents various methods for assessing and quantifying the flexibility of power systems. By doing so, Section 2 establishes the connection between the non-covered aspects of adequacy assessment methods and the field of flexibility, providing a comprehensive understanding of the challenges faced in maintaining a reliable power system operation while ensuring flexibility requirements.

2.1. Assessing the individual contributions to power system adequacy

The capacity value¹ is a metric that shows how much a technology contributes to meeting power system reliability standards. Existing metrics for assessing the individual contributions to power system adequacy attribute a coefficient that reflects the availability of generation units to maintain reliability standards during peak load demand periods [17].

The various existing methods for computing capacity value can be aggregated into two groups: those based on reliability measures and those based on approximations [17]. Reliability-based methods for assessing the contribution of technologies to the power system, such as Equivalent Firm Capacity (EFC) and Effective Load Carrying Capability (ELCC) [13], are widely used. Approximation methods such as the capacity factor approximation-based method estimate capacity by averaging a technology's capacity factor over a determined number of critical hours of load demand or net demand,² depending on the share of VRES in the power system.

Authors in [18] show that the capacity factor approximation-based method is the one whose results most closely approximate those obtained from a reliability-based method. Although this method remains sensitive to the number of hours considered and the electricity system studied [18], it is now being used in the industrial field [19] and in academic cases [8]. Authors in [8] average the capacity factor of Energy Storage Systems (ESSs) over critical hours of net demand to determine how ESSs could replace thermal units as a peaking capacity. In Mexico, the SO calculates capacity based on the historical output of technologies in the most critical 100 h of the year [19].

However, assessing the adequacy of power systems based solely on capacity value fails to consider the flexible behaviour of technologies [3]. Indeed, authors in [20] point out that integrating VRESs, increases the net load ramps and operating reserves. Besides contributing to power system adequacy, flexible technologies can help the electricity system cope with variability and uncertainty arising from several power system scarcities. Therefore, an assessment of individual contributions to adequacy should include variability and uncertainty aspects in the energy transition context [21].

After presenting the limitations of the capacity value methodologies, the next section lists the power system scarcities that adequacy assessment should consider.

2.2. Power system scarcities

A strong presence of VRESs in power systems may lead to critical parameters such as ramps, hourly power, and energy (i.e., several consecutive hours), as pointed out in [22]. This section provides an in-depth analysis of operational scarcities that may arise in such power

¹ Also called capacity credit [14], firm capacity [15], firm supply [16].

² Load demand minus non-dispatchable generation.

systems in the medium-term, where installing new capacity is not feasible.

Ref. [22], listing the challenges posed by the deployment of storage in scenarios of high renewable energy penetration, highlights that forecasting errors will be subject to more uncertainty, which impacts the volume of operating reserves. Although operating reserves are calculated on a sub-hourly time scale, Ref. [23] recommends that this aspect be considered when analysing the behaviour of ESS technologies in the medium-term. In line with this, using a medium-term operating model, the authors in [24] have shown that considering operating reserves incentivised the participation of batteries in producing energy and operating reserves.

Moreover, dispatchable technologies must have sufficient ramps to adapt to the inherent variability of non-dispatchable VRES output [25]. Hourly ramps indicate the difference in power output between two consecutive time steps. An indication of the significance of considering ramps as part of the power system's criticality lies in the ongoing research devoted to developing ramp-level indicators. Authors in [26] proposed the insufficient ramping resource expectation (IRRE) metric to assess the risk of ramping resource shortages as complementary metrics when assessing power system adequacy. The authors aimed to better understand power system flexibility and enhance planning decisions amidst increasing renewable energy integration, ensuring a reliable power supply. Authors in [27] analysed the impact of VRES on the operation of the ERCOT grid (Electric Reliability Council of Texas) according to the ramp of the net load. They observed that strong solar PV integration impacts hourly ramping and ramping volatility of net demand.

Another aspect that becomes critical as the share of VRES increases is hourly power. "Power" refers to the instantaneous power produced by a generating unit, but reliability studies generally adopt an hourly time resolution by approximating the instantaneous power to the average power produced over one hour [2]. Authors in [28] show that the difference between the maximum and minimum net hourly load demand in a year increases as the share of VRES increases. Thus, hourly power output defines the scarcity in dispatchable power available.

Additionally, energy storage requirements are expected to increase as the share of VRES increases [6]. Moreover, there are storage needs on several time scales [29]. For example, a system based exclusively on solar production mainly needs daily storage. By contrast, a system based on energy, such as hydropower technology, has seasonal storage needs, with the Brazilian power system as a case in point [30]. Thus, energy requirements might be part of power system scarcities in high VRES scenarios. Several references seek to determine the need for storage based on the current share of VRESs. For example, in [8], authors identified storage requirements according to both VRES shares and peak load demand.

Therefore, given that several aspects of the electricity system become critical as the share of VRESs increases, flexible technologies traditionally used for maintaining the SoS of power systems will face changes in their dispatch [8]. For high VRES shares, traditional adequacy assessment studies as mentioned in 2.1, omit the critical aspects highlighted in this section. Section 2.3 presents the aspects of flexibility which are not currently considered in adequacy studies but are necessary in the case of renewable-dominated power systems.

2.3. Dimensions of flexibility

A correct assessment of flexibility should cover several aspects by answering the following three questions: how inflexible are power systems? How much flexibility do power systems have? Who provides flexibility when needed?

This section details how the various flexibility questions are commonly addressed.

How inflexible are power systems? Several references analyse scarcity aspects of net demand such as operating reserves [31], ramps [26],

power [12] and energy [8]. Indeed, a complete net demand analysis highlights the flexibility that technologies will be required to provide. Thus, assessing the inflexibility of a system is equivalent to assessing its flexibility requirements.

How much flexibility do power systems have? Comparing the flexibility of different technologies requires the same measures to be applied across technologies, but the methodology for each technology follows a different approach [32]. Indeed, the flexibility of thermal units is mainly based on static parameters (e.g., installed power, ramp rates, minimum power output, and energy storage capacity). By contrast, historical values must be considered in the case of hydropower technologies since their capabilities depend on the seasonal nature of water inflows. VRES and non-dispatchable units are inflexible by nature or historical operation since they depend on meteorological conditions or restricted operations [33]. Although VRES curtailment could be considered a flexibility aspect of power systems [34], this option is not contemplated in the presented paper. Generally, the opportunity cost of curtailing renewables is high, i.e., some renewable generation is wasted, and this can only be justified in limited conditions where alternatives are more costly.

Who provides flexibility when needed? Power systems can have a heterogeneous mix, so measures of contributions to flexibility must be defined for each technology separately. Authors [32] quantify contributions to flexibility at different timescales, analysing the behaviour of technologies in modulating their upward and downward outputs. Ref. [28] apply the same method as in [12] to assess contributions to flexibility in high VRES scenarios in Japan and Sweden. An analysis of contributions to flexibility would be helpful to support the development of regulation of operational flexibility services, but there is a lack of references [32].

To summarise Section 2, on the one hand, Ref. [21] recommends analysing flexibility when assessing power system adequacy. On the other hand, the European Commission suggests analysing flexibility according to different time scales [29]. Therefore, following these recommendations, Section 3 details the methodology developed and used in this paper to simultaneously assess the contributions of technologies to power system adequacy and the different aspects of flexibility on different time scales.

3. Methodology

This section provides a comprehensive explanation of the methodological approach proposed, graphically summarised in Fig. 1. The methodology aims simultaneously to determine flexibility requirements, contributions of technologies to flexibility, and their contributions to the adequacy of the system. The proposed methodology is also scalable and replicable for several scarcities and can be generalised to any electricity system since only hourly time series (i.e., load demand, VRES outputs, generation and storage technical characteristics) are required as inputs.

The methodology involves three main steps, further detailed. Firstly, the ex-ante analysis (Section 3.2), represented by the dotted box in Fig. 1, focuses on deriving flexibility requirements. Next, running a medium-term operation model (Section 3.3) to reproduce power system operation with a one-year time scope. Finally, the ex-post analysis of model outputs (Section 3.4), represented by the dotted box in Fig. 1, to calculate capacity values and contributions to flexibility. Capacity values are obtained using the capacity factor approximation-based method reference in [18] and contributions to flexibility are calculated based on the method proposed in [32].

The time series decomposition module provides the requirements for, and contributions to flexibility, which are assessed on several relevant time scales using a frequency analysis method originally presented in [35] and further adapted to hourly time step in [12]. The idea of the time series decomposition module consists of two steps. Firstly, analysing what the different relevant time scales present in the

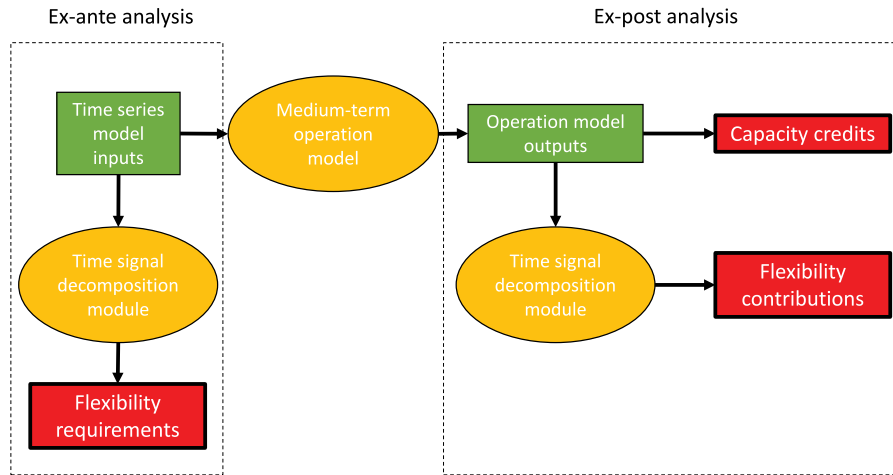


Fig. 1. Overview of the methodology for assessing flexibility and capacity value simultaneously.

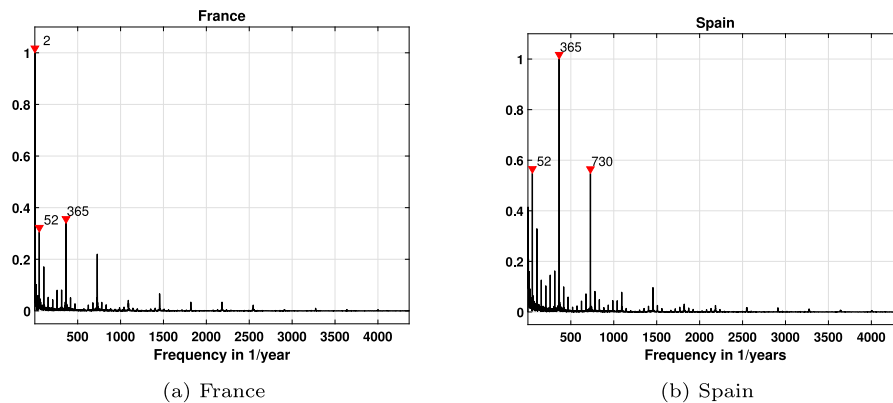


Fig. 2. Hourly load demand in the frequency domain for different power systems in 2019 [36]. Red triangles signal the highest frequencies and their corresponding cycle number. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

load demand and technology outputs are. Secondly, it calculates the distribution of the variations present in the distinct periodicities.

The methodology proposed addresses the requirement of the European Commission [29] to analyse flexibility aspects on several time scales and responds to the exigency of considering flexibility aspects when assessing the power system adequacy [21].

3.1. Time signal decomposition

Although they are variable and uncertain, load demand and VRES output show periodic cycles (e.g., hot and cold seasons, day and night, work days and weekends). The associated periodicities are sufficiently deterministic for frequency analysis methods to be applied, such as the Discrete Fourier Transform (DFT) [12].

The DFT is a mathematical transformation to change a time-discrete signal to its frequency-discrete representation. Eq. (1) represents the formulation for obtaining the discrete frequency-domain components ($X[k]$) as a function of the discrete time-domain samples ($x[n]$), where N stands for the number of samples in the series, and n and k represent the discrete time and frequency index, respectively. Thanks to this operation, frequencies with a higher representation in the signal can be identified by their higher amplitudes.

$$X[k] = \sum_{n=0}^{n=N-1} x[n] \cdot e^{-j \frac{2\pi nk}{N}} \quad (1)$$

Fig. 2 shows the DFT of the annual load demand time series (i.e., 8760 h) of different power systems [36]. The horizontal axis

represents frequencies in $\frac{1}{\text{year}}$ and reflects the pseudo-periodicity of an event. The vertical axis is normalised for the strongest frequency component and represents the intensity of each frequency. In Fig. 2, all plots show a strong periodic component at 52, 365, and 730 $\frac{1}{\text{year}}$, representing the weekly (i.e., 52 oscillations in a year), daily (i.e., 365 oscillations in a year) and 12-hours (i.e., 730 oscillations in a year) periods. However, these cycles differ in intensity according to the power system considered. In the case of France the highest frequency is 2, showing that there are two major cycles per year. The summer-winter seasonal cycle is highly pronounced due to the substantial proportion of electrical heating. In the case of Spain the seasonal pattern is less marked than in France, but the cycle with 365 periods corresponding to the daily patterns is more significant in relative terms.

Three bandpass filters are applied to the frequency signal to extract the relevant components as in [12,35]. In Fig. 3(a), each colour represents the component of the spectrum that is filtered and assigned to the corresponding signal: weekly, daily and 12-hours (i.e., the blue, red and green boxes respectively in Fig. 3(a)).

The pseudo-periodicity of the signal justifies the adoption of periodic bandpass filters. Indeed, the spectrum of the daily component can be expected to be concentrated around multiples of the 365 $\frac{1}{\text{year}}$ frequency. This is because periodic functions can be mathematically represented by a discrete spectrum (also known as Fourier Series [37]) with the energy allocated at multiples of its fundamental frequency (i.e., the inverse of the signal's period). The same principle can be applied to the 12-hours component, but for multiples of 730 $\frac{1}{\text{year}}$ frequency.

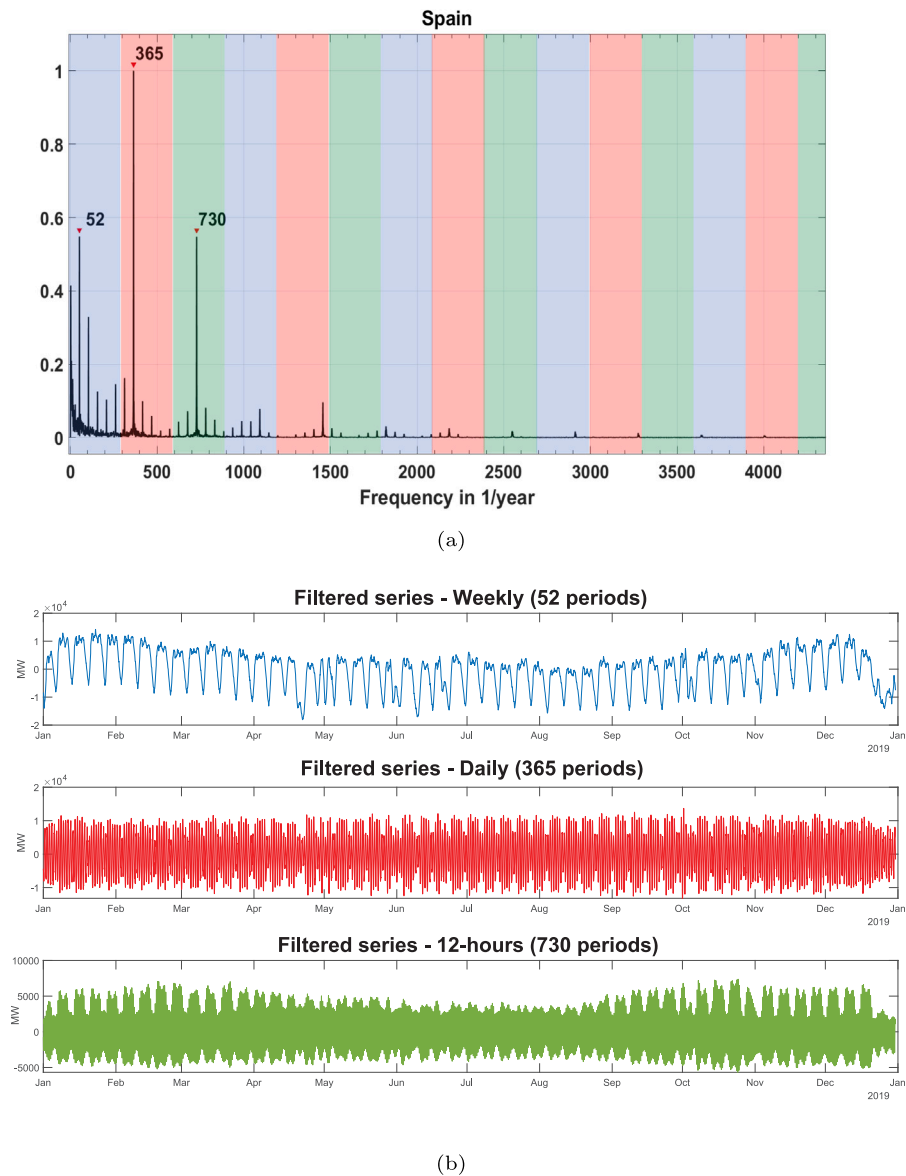


Fig. 3. (a) Three bandpass filters for separating weekly (blue blocks), daily (red blocks), and 12-hours signals (green blocks); (b) Filtered time series obtained using IDFT on relevant frequencies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The width of the bandpass filter remains a sensitive issue. Indeed, given that the sum of the signals will always result in a very small error, there is no clear optimum for determining at what frequency to cut. The authors in [12,28,32] use a slightly different method, but they defend the width of their bandpass filter on the basis that the results obtained were satisfactory. Therefore, in this paper, in line with the Spanish power system, the bandwidth is set at $120 \frac{1}{\text{year}}$.

As a final step, once the spectrum bands corresponding to each component are selected, each signal is transformed back to the time domain with an Inverse Discrete Fourier Transform (IDFT), which carries out an operation inverse to that of the DFT. Fig. 3(b) shows three time-domain signals, each corresponding to one of the different components under study.

3.2. Assessing operational flexibility requirements

Once hourly load demand is expressed according to different time scales, flexibility requirements are based on the distribution of the maximum variations during each signal cycle (i.e., 52 values for the weekly signal, 365 values for the daily signal and 730 values for the 12-hours

signal) as in [12,28]. The measure of flexibility requirement considers the hourly time series of load demand over a one-year period. Note that this measure applies to several scarcities in electricity systems, such as ramps, the energy required for a period and operating reserves.

As an example, Fig. 4 presents the operational flexibility requirements according to hourly load demand (blue), hourly load demand minus hourly solar PV output (yellow), hourly load demand minus hourly wind output (purple), and net hourly demand (i.e., load demand minus wind and solar PV) (red). Boxplots show the distribution of the different filtered time series according to the maximum variation observed in each period of signals. (e.g., the weekly boxplot includes 52 values corresponding to the maximum variation in hourly values observed each week of the year, and so on for other signals).

According to Fig. 4, solar PV output shows more variability than wind on the 12-hours time scale, while the reverse is true for the daily and weekly signals. So solar PV causes the 12-hours variability while wind is the main cause of the daily and weekly variability. Moreover, the maximum variation of solar PV is similar for the 12-hours and daily signals, while that of wind shows a greater difference. In the case of the Spanish power system in 2019, the larger the time scale considered, the

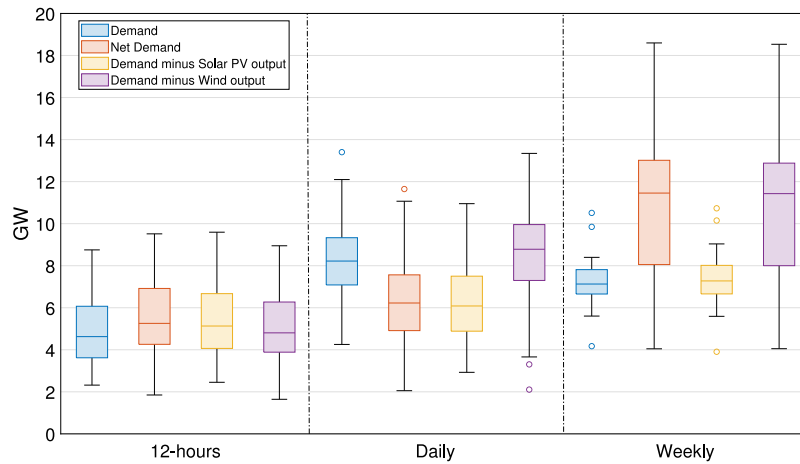


Fig. 4. Operational flexibility requirements in power for the Spanish electricity system in 2019 [38].

more wind variability impacts the operational flexibility requirements. This can be explained by the fact that in 2019 the share of wind energy in the Spanish electricity system was higher than that of solar PV. Thus, this paper analyses net load demand and its components to study how technologies maintain adequacy and provide flexibility to power systems in a scenario with high VRES shares. These results are relevant for analysing alternative future scenarios where the ratio between wind and solar changes and therefore so do the expected flexibility requirements in different time frames.

3.3. Operation model

It should be possible to analyse the flexible behaviour of technologies using historical data, but the future generation mix will change dramatically as new technologies will form part of the energy mix by 2030 and the ratio between technologies will change; the operational roles of technologies are therefore also likely to change. Moreover, the ESS mix will be heterogeneous and references [23] recommend using a medium-term time scope for comparing ESS operation in scenarios with high VRES shares. Therefore, analysing how different dispatchable technologies such as batteries and PSH maintain power system reliability and provide flexibility in services requires a medium-term time scope to be adopted.

This paper assesses the operational flexibility and capacity values of technologies based on the results obtained from the Spanish Electricity and Economic Dispatch (SEED) model developed in [24]. It is important to note that operation models such as openTEPES [39] and PLEXOS [40] could be perfectly interchanged with SEED as part of the methodological approach presented in this article. Indeed, the results obtained with SEED are similar to those obtained with openTEPES presented in [39]. OpenTEPES is the operation and expansion planning model used to update the latest draft proposal of the Spanish National Energy and Climate Plan [41].

SEED is a hydrothermal medium-term operation planning model which splits ESSs according to the recommendations of the Agency for the Cooperation of Energy Regulators [21]. Given that a medium-term time scope is recommended for comparing the operational abilities of technologies such as batteries and PSH [24], SEED reproduces the centralised operation of an electricity system on an hourly basis over a time scope of one year (i.e., 8760 h). The SEED model also considers hourly load demand with provision for operating reserves³ (i.e., balancing capacity and balancing energy). The volume of balancing capacity

³ Although some balancing services are provided on a sub-hourly basis, it is common to incorporate them into operation models with a time step of one hour, under the framework of operating reserves [33].

activated to provide balancing energy is based on a constant percentage estimated from historical data as in [42]. The main model outputs include hourly output in energy and balancing services, curtailment, and monitoring of water reservoir and energy storage levels.

Finally, given that the proposed approach considers no investment option, this paper cannot highlight the impact of the measures of contributions to flexibility and adequacy on future investments. However, this paper could extend the study by [15], which analyses the impact of capacity values on investment decisions.

3.4. Assessing contributions to operational flexibility

Once the hourly outputs of the economic dispatch of the generation and storage technologies are obtained from the operational model, they are filtered through the time series decomposition module to extract the flexibility contributions as in [28,32]. Contributions of technologies to flexibility are based on the distribution of the variation of the technology dispatch output from peak to average values during each signal period considered. Contributions to operational flexibility are expressed as the ratio of the changes in the output of the technology to net demand. This reveals how technology changes from its average behaviour on different timescales to various power system scarcities. Thus, this operational flexibility measure is quantitative and should be interpreted as the flexible behaviour of a technology to adapt to variations of scarcities of the electricity system. However, net demand shows many minor variations due to the output of VRES, so a threshold of 20% is applied to remove minor variations in the hourly net demand [32].

Fig. 5 illustrates the contributions to flexibility of dispatchable technologies in the Spanish power system in 2019 [36]. Fig. 5 presents the distribution of the contribution to flexibility of each technology according to different time scales.

Boxplots show how technologies adapt their output power to variations in net demand (e.g., considering only variations greater than 20% of the maximum value of net demand). Some boxplots show a contribution that can exceed 100%. This is the case when a technology changes its power output beyond variations in net demand. Relative to all time scales, Combined Cycle Gas Turbines (CCGT) are the biggest provider of flexibility across all technologies. As shown in Fig. 5, coal technology is less flexible than CCGT and ESS. Thus, coal technology contributes less to flexibility in the Spanish electricity mix in 2019. One reason is its high variable cost. Secondly, coal generation units have a slower ramp rate than other dispatchable technologies. However, although the flexibility contribution remains low, it increases as the time scale considered lengthens

As shown in Fig. 5, Storage Hydro technology makes a greater contribution to flexibility than CLPSH. Indeed, Storage Hydro units

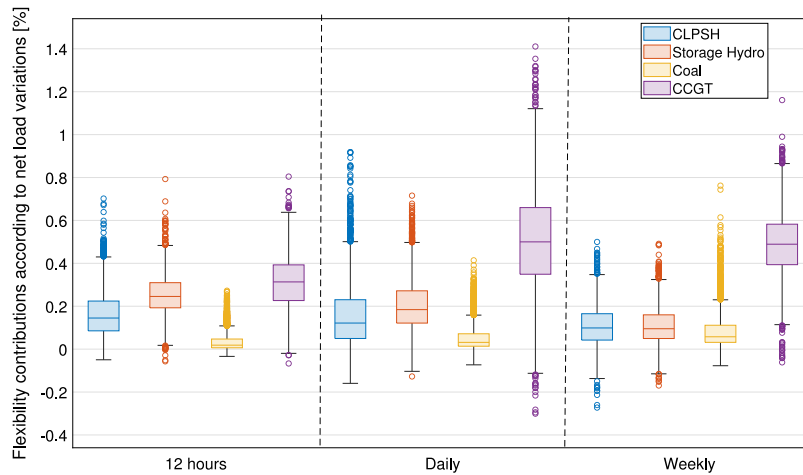


Fig. 5. Operational flexibility contributions of dispatchable technologies according to net load variations in power for the Spanish electricity system in 2019 [38]. Here data for OLPSH and Hydro Storage are only available in aggregate.

have higher energy storage capacity and higher installed capacity than CLPSH, so they are more able to adapt their output to net demand variations.

3.5. Limitations

The methodological approach proposed experiences some limitations.

This paper only considers flexible technologies that have reached technological maturity. Therefore, emerging technologies such as electric vehicles, power-to-X, demand response, and hydrogen-based systems are ignored. Further research is needed for accurate assessment and integration of these technologies.

Another limitation is the exclusion of network constraints in the model. Indeed, considering network flexibility may enhance results, providing a comprehensive understanding of the flexibility contribution of technologies within interconnected power grids.

Additionally, the hourly temporal resolution limits the ability to capture sub-hourly variations critical for comprehending power system flexibility dynamics.

Lastly, the operation planning model is deterministic. Using stochastic methods and building extreme scenarios would enable extremely flexible behaviour of technologies to be observed.

Although limited, the conceptual framework and the model proposed could be enhanced. However, this paper addresses the dilemma faced by technologies in providing flexibility in services, adequacy or both.

4. Case study and scenarios

This paper applies the methodology presented in Section 3 and analyses how different technologies will supply flexibility services and maintain the adequacy of the Spanish power system by 2030, according to the Spanish NECP. All scenarios analysed are based on open access data provided by the Spanish SO [38]. Table 1 presents the reference case (*Ref Case*) based on Spain's NECP [6].

The installed capacity proposed by the Spanish NECP and studied in the *Ref Case* appears to be sufficient to meet the load demand, but what would happen if solar and/or wind VRES generation were to be unavailable for a time for meteorological and/or technical reasons? This sensitivity is studied in the Ten-Year Network Development Plan (TYNDP) 2022 [23] and is called *DunkelFlaute* ("dark period" in German). Under the TYNDP method, the *DunkelFlaute* scenario considers two weeks of a year coinciding with high load demand and a total absence of wind generation. Although this scenario is not based on

historical data (i.e., two weeks of high load demand have never actually coincided with two weeks of low wind generation), it highlights the impact of anticyclonic gloom⁴ on the operation of electrical systems. Thus, this paper proposes a *DunkelFlaute*-sensitivity scenario built up following the method proposed by the authors in [23]. In this paper, the two weeks of low wind start in the fifth week of the year according to the time series used. Therefore, in the two weeks when the load demand is the highest, the wind power output is reduced to its historical lowest capacity factor (6% according to the 5th percentile).

Additionally, the Spanish electricity system strongly relies on hydropower output [38]. Water inflows in Spain show inter- and intra-annual variability, so flexible technologies that do not depend on water inflows must adapt their dispatch to maintain the system's security in the medium-term. Therefore, this paper explores sensitivity scenarios according to different water inflow scenarios. Sensitivity scenarios are built up on the *Ref Case*. *Wet Case* and *Dry Case* are based on the annual weekly profile of 2016 and 2017, respectively, with 34.5 TWh and 15.9 TWh of hydropower inflows, while the *Ref Case* is based on the annual weekly profile of 2015, which is considered an average water inflow scenario with 25.1 TWh. Table 2 summarises the main parameters of the scenarios analysed in this article.

As recommended in [33], this paper considers the technical features of all ESSs to assess their operation in the future mix at unit level. Thermal power plants are also modelled as market units. They are characterised by their installed capacity (MW), Equivalent Forced Outage Rate (EFOR) based on historical values, emission rate and variable cost parameters. VRES technologies (Wind and Solar PV) do not have variable costs and follow hourly generation profiles based on 2015. ESS technologies such as Pumped Storage Hydro (CLPSH and OLPSH) and battery are defined by installed power capacity (MW), Expected Forced Outage Rate (EFOR) (%), energy storage capacity (MWh), maximum time discharge cycle (hours) and roundtrip efficiency (%). Storage Hydro technology is defined with the same parameters as ESS except for roundtrip efficiency since Hydro Storage units cannot pump. This study does not consider the effect of cross-border interconnections.

5. Results and analysis

Given that dispatchable technologies such as ESSs can provide several services according to different power system scarcities, an analysis

⁴ The *DunkelFlaute* scenario defines a meteorological phenomenon in Europe's North Sea, but can represent a complex situation for maintaining reliability standards in the Iberian peninsula.

Table 1
Spanish electricity system, according to [6,24].

Technologies	Installed power capacity (# programming units considered) (MW)	Installed pump capacity (MW)	Energy storage capacity (GWh)	Cycle Discharge (Seasonal/Weekly/Daily)	Roundtrip efficiency (%)	Variable Cost (€/MWh)	Emission rate (€/MWh)	OM Variable cost (€/MWh)
Nuclear	3050(3)					23	0	0
CCGT	24,560(50)					40	0.33	2
Cogeneration	3980					0	0.575	0
Solar PV	38,404					0	0	0
Solar Thermal	7300					0	0	0.46
Wind Onshore	48,550					0	0	0
Storage Hydro	7500(53)		9780	Seasonal		0	0	0
No Storage Hydro (Run-of-River)	1303					0	0	0
OLPSH	7750(4)	2114	6208	Seasonal	0.75	0	0	0
Existing CLPSH	3648(10)	3552	120	Weekly/Daily	0.75	0	0	0
PCI I	235	235	1.5	Daily	0.79	0	0	0
PCI II	3400	3400	27.2	Weekly	0.79	0	0	0
PCI III	552	548	3.67	Daily	0.78	0	0	0
Batteries	2500	2500	10	Daily	0.9	0	0	0
Other RES	1730					0	0	0

Table 2
Overview of base case and sensitivity scenarios based on the Spanish NECP [6].

	Ref Case	Wet Case	Dry Case	Dunkelflaute
Water inflows (TWh)	25.1	34.5	15.9	25.1
Wind annual generation (TWh)	118.090	118.090	118.090	112.153

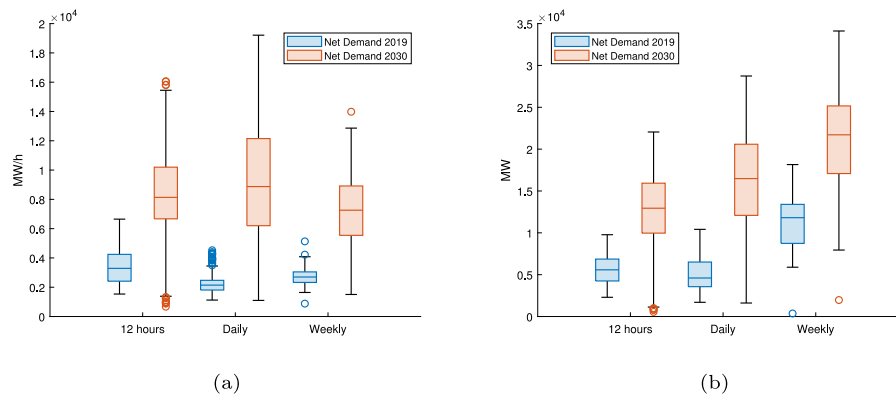


Fig. 6. Operational flexibility requirements in ramps (a), and power (b), according to net load demand in 2019 and 2030 for the Spanish electricity system.

of how they maintain adequacy and provide operational flexibility is required. Therefore, according to the focus of the study, this assessment considers the (1) operational flexibility requirements on different time scales according to ramps, power and operating reserves; (2) contributions to operational flexibility; and (3) contribution to adequacy during critical periods. Given that the model optimises the system operation, the results reflect the best contributions to flexibility from that point of view.

5.1. Operational flexibility requirements

Operational flexibility requirements are assessed on three relevant time scales and according to several scarcities in power systems in scenarios with high VRES shares. Fig. 6 shows the operational flexibility requirements on different time scales for *Ref Case* and the Spanish power system in 2019.

According to Fig. 6, operational flexibility requirements in ramps (Fig. 6(a)) and power (Fig. 6(b)) are set to increase in the Spanish electricity system by 2030. Indeed, distributions of flexibility requirements on several time scales are higher in *Ref Case* than in 2019. Of all the signals in Fig. 6, it is the daily signal distribution that increases the most. This is because solar PV is the technology that will increase the most between 2019 and 2030.

Additionally, in Fig. 6(b), the ranking between the weekly, daily and 12-hours flexibility requirements changes from 2019 to 2030. According to *Ref Case*, daily and 12-hours flexibility requirements had similar distributions in 2019, but the median of the distribution of the daily requirements is 30% higher than for 12-hours flexibility requirements.

The same goes for the ramps in Fig. 6(a) except for the weekly signal. The weekly signal shows the biggest variation in terms of flexibility requirements in power, but the smallest variation in terms of flexibility requirements in ramps. This means that the variation in the ramps within a week does not change significantly from week to week within a year.

The increase in flexibility requirements is explained by the sharpening of the critical parameters of the net demand caused by the large-scale introduction of VRES. Indeed, according to the results of *Ref Case*, the gap between the minimum and the maximum hourly values of net demand within one year is 39% higher in 2030 than in 2019. Additionally, the size for each time signal increases considerably as the share of VRES increases.

Although sensitivity scenarios explore the impact of changes in water inflows on electricity system operation, flexibility requirements in *Wet Case* and *Dry Case* are similar to the *Ref Case*. Indeed, a change in water inflows impacts the power system's ability to respond to flexibility requirements. However, the flexibility requirements of the

Table 3
Indicators of power system operations for the *Ref Case* and the sensitivity scenarios.

		<i>Ref case</i>	<i>Dunkelflaute</i>	<i>Dunkelflaute/Ref</i> [%]	<i>Wet Case</i>	<i>Wet/Ref</i> [%]	<i>Dry Case</i>	<i>Dry/Ref</i> [%]
Total operation cost	M€	3,559	3,922	9%	3,130	-14%	3,960	10%
Curtailement	%	10%	10%	1%	11%	14%	8%	-20%
VRES Shares	%	78%	76%	-2%	80%	3%	76%	-2%
CCGT	GWh	31,154	36,546	15%	24,747	-26%	37,090	16%
Storage Hydro	GWh	12,452	12,452	0%	16,685	25%	8,582	-45%
OLPSH	GWh	13,153	13,009	-1%	17,561	25%	10,228	-29%
Existing CLPSH	GWh	4,560	4,319	-6%	4,818	5%	4,664	2%
New CLPSH	GWh	5,793	5,624	-3%	5,993	3%	6,026	4%
Battery	GWh	2,838	2,771	-2%	2,901	2%	2,959	4%

power system (i.e., demand, VRES profile, operating reserves) are not impacted in the sensitivity scenarios.

In the case of the *Dunkelflaute*, the absence of wind during the two weeks of highest demand impacts the flexibility requirements (net demand is greater than in the *Ref Case*), but its greatest impact is on capacity.

5.2. Contributions to operational flexibility

The initial approach to assess which dispatchable technology offsets the lack of wind (the *Dunkelflaute* scenario) or water inflows (*Dry Case*) is to compare the output per annum in the different scenarios. In addition, the levels of curtailments, the share of VRES and the total operating costs give an overall indication of the operational flexibility of the power system. Table 3 presents these medium-term power system operation indicators obtained for the *Ref Case* and the sensitivity scenarios (*Dunkelflaute*, *Wet Case* and *Dry Case*).

The *Wet Case* shows the biggest variation from the *Ref Case* according to the total operating cost. Indeed, given that natural water inflows are higher, Storage Hydro and OLPSH outputs increase while CCGT use decreases, thus lowering the total operating cost.

Additionally, the output of battery and CLPSH technologies is higher in the *Wet Case* and the *Dry Case* than in the *Ref Case*. In the *Dry Case*, batteries and CLPSHs increase their output to offset the reduction in Storage Hydro and OLPSH output. In the *Wet Case*, batteries and CLPSHs increase their output to limit the use of CCGT and reduce the total operating cost.

According to the results shown in Table 3, in comparison to the *Ref Case*, the operational impacts of the *Dry Case* and the *Dunkelflaute* scenario are similar in terms of total operational costs and changes in the electricity output from technologies. However, these impacts might be due to different reasons. Figs. 7(a) and 7(b) explain this observation by showing the electricity system operation during the two weeks of no wind (i.e., as the result of the *Dunkelflaute* scenario) for the *Ref Case* and *Dunkelflaute*, respectively. In the *Dry Case*, the difference in output occurs throughout the year when CCGT technology offsets the lack of water inflows. In the *Dunkelflaute* scenario, technology outputs change in the two weeks of no wind.

Table 4 shows the share of technologies in supplying upward and downward operating reserves. The installed capacity of batteries is the smallest of the dispatchable technologies in the *Ref Case*, but battery technology participates to a similar extent to Storage Hydro in the supply of operating reserves. This is because operational reserves represent power sizes and energy volumes that are much smaller than demand. Thus, by participating significantly in operational reserves, batteries allow other ESS to have their energy reserves fully available for the most critical events.

To complete these medium-term system operation indicators, the paper also shows how each technology contributes to the flexibility of the electricity system on different time scales. Fig. 8 shows the contributions to operational flexibility of dispatchable technologies according to power scarcity for the *Ref Case*.

Table 4
Shares of technologies in supplying operating reserves upward and downward for the *Ref Case*.

	Up	Down
CCGT	8%	16%
Storage Hydro	17%	17%
OLPSH	19%	12%
CLPSH	18%	17%
New CLPSH	22%	20%
Battery	16%	17%

As shown in Fig. 8, the ranking of signals is different for each technology. Storage Hydro, existing CLPSH, OLPSH and CCGT show higher contributions to flexibility in the weekly signal than the daily and 12-hour signals while new CLPSHs and batteries show higher contributions in the daily and 12-hours signals. The difference in the contributions to flexibility of the different ESSs is mainly due to the discharge cycle available to each ESS: Storage Hydro, existing CLPSH and OLPSH have a discharge cycle ranging from one week to one season, whereas batteries have a discharge cycle of one day and new CLPSHs range up to one week. The discharge cycle limits ESS in its energy reserve management. Thus the contribution to flexibility from ESSs is mainly determined by the discharge cycle.

Furthermore, comparing all technologies and given that battery technology has a small installed capacity, batteries are the technology that contributes least to operational flexibility according to power scarcity. Conversely, and in accordance with [32], CCGT provides the highest power modulation under all three timescales. Other technologies, such as existing CLPSH, OLPSH and Storage Hydro, contribute to operational flexibility in power in similar proportions.

The results concerning contributions to operational flexibility on different time scales for the sensitivity scenarios are not shown since no considerable differences were observed.

5.3. Contributions to adequacy: capacity value

The contributions of technologies to adequacy are obtained using the capacity factor approximation-based method [18]. The paper focuses on analysing which technologies provide adequacy in scenarios with high VRES shares, so the capacity factor approximation-based method is related to the hours of highest net demand. Thus, contributions to adequacy are assessed according to critical periods where high demand and low VRES output could coincide. Table 5 shows the capacity values of the dispatchable technologies based on 100, 200 and 400 h of the highest net demand values (i.e., critical hours) for the *Ref Case*.

The results shown in Table 5 are obtained relatively from the *Ref Case* and the modelling assumptions. In line with the contributions to adequacy shown in Table 5, batteries are the last dispatchable technology to provide adequacy during critical periods. Additionally, the contribution to adequacy of new CLPSH is lower than that of

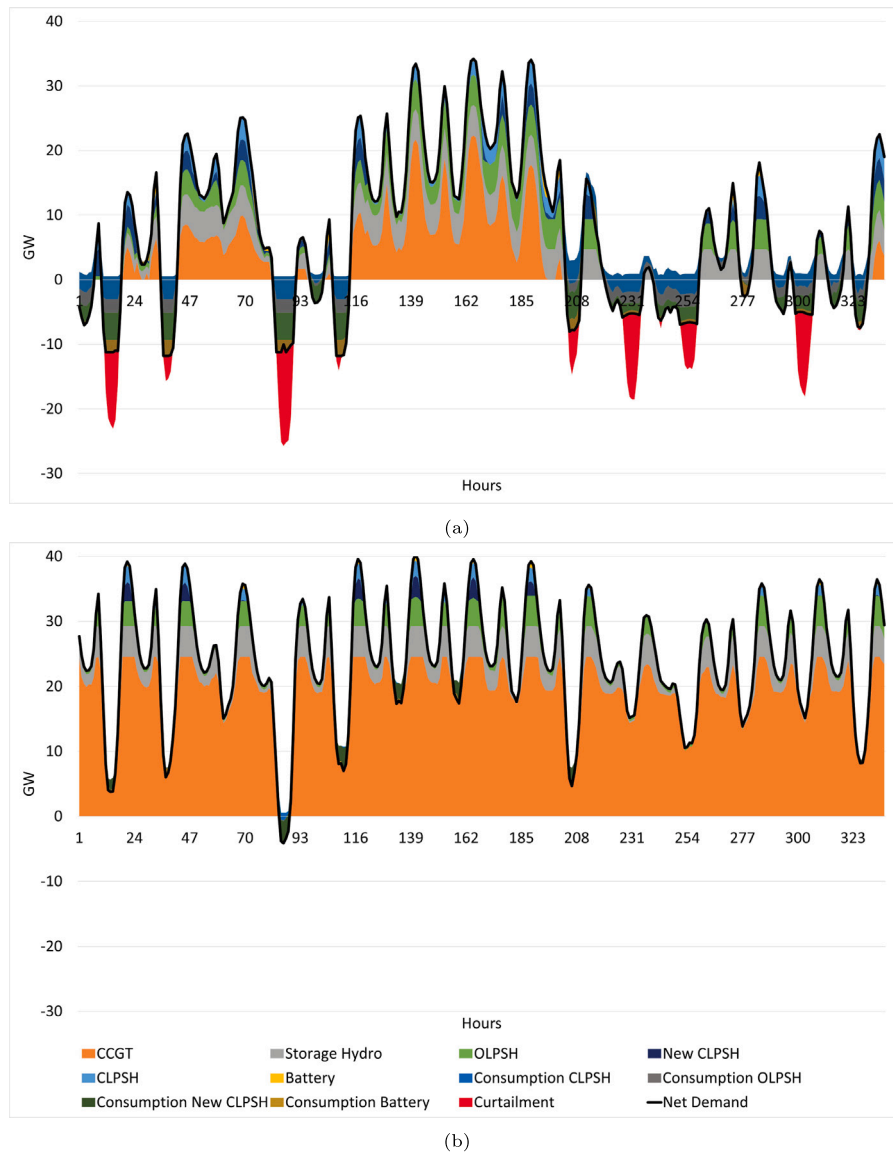


Fig. 7. Hourly output of technologies during the two weeks when demand is the highest for the Ref Case 7(a) and the Dunkelflaute scenario 7(b).

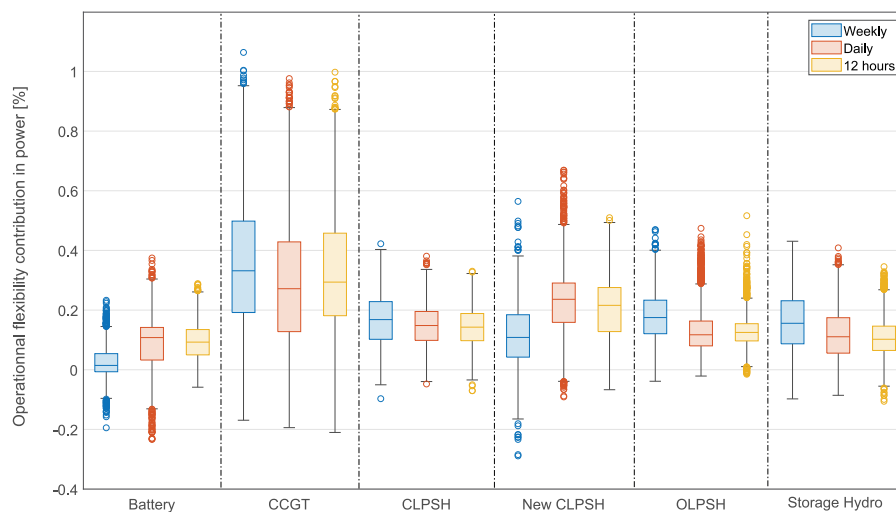


Fig. 8. Operational flexibility contribution in power according to the net load variations for the Ref Case.

Table 5
Capacity value of technologies according to different time ranges for the *Ref Case*.

	Battery	CLPSH	OLPSH	NEW CLPSH	CCGT	Storage hydro
100 critical hours	6%	63%	88%	27%	74%	98%
200 critical hours	7%	62%	82%	34%	66%	94%
400 critical hours	13%	58%	77%	40%	57%	89%

Table 6
Capacity value of technologies according to the average of 100–400 critical hours of net demand for the *Ref Case* and sensitivity scenarios.

	Battery	CLPSH	OLPSH	New CLPSH	CCGT	Storage hydro
<i>Ref Case</i>	9%	61%	82%	35%	65%	93%
<i>Dunkelflaute</i>	12%	56%	81%	35%	69%	93%
<i>Dry Case</i>	9%	60%	69%	34%	71%	79%
<i>Wet Case</i>	9%	66%	93%	36%	62%	92%

existing ones. New CLPSHs have a higher roundtrip efficiency than existing ones, but their discharge cycle is shorter and their energy storage capacity is lower. Therefore, it seems that the higher the energy storage capacity (e.g., 33 h of discharge at full power for existing CLPSH and 8 h for new CLPSH), the higher the contribution to adequacy (63%–58% for existing CLPSH and 27%–40% for new CLPSH). Authors in [14] observe the same result. Moreover, as shown in Table 6, the capacity value of some technologies increases and others decrease according to the different scenarios. When the range of critical hours used to calculate capacity value decreases and the resulting capacity value increases, it shows which technology to rely on for maintaining the system's reliability during critical periods.

Capacity value is also calculated for sensitivity scenarios. Table 6 shows the averaged capacity value of technologies in the 100 to 400 critical hours for the *Dunkelflaute*, *Dry Case*, and *Wet Case*. Batteries appear to be the last available technology during critical hours, but they tend to be the technology with fewest variations between sensitivity scenarios according to its capacity value. This is because batteries have less energy storage capacity than the other ESSs.

6. Conclusions

This paper presents a conceptual framework and methodology for jointly assessing the adequacy and operational flexibility of the Spanish power system in 2030. It applies the methodology to sensitivity scenarios to highlight how the contributions to adequacy and flexibility of each technology behave in line with critical parameters such as water inflows and wind scarcity. A medium-term operation planning model is used to represent the centralised operation of the Spanish power system in scenarios of high VRES shares. The modelling considers the supply of balancing services, so contributions to operational flexibility can also be assessed according to operating reserves. Such contributions are also assessed according to several relevant timescales.

Regarding contributions to flexibility, CCGT is the most flexible technology over all time scales in the energy mix of the Spanish system in 2030, but it is a transition technology and its installed capacity would be limited in future scenarios. However, a comparison of contributions by ESS to flexibility reveals that new CLPSH technology provides most of the operational flexibility on the daily time scale, mainly because its installed capacity and roundtrip efficiency are higher than those of existing CLPSH. Due to their small installed capacity and limited energy storage capacity, batteries provide only a small fraction of the operational flexibility in power. However, regarding contributions to flexibility in operating reserves, batteries have a more critical role in providing energy than other flexible technologies. Thus, battery technology provides operational flexibility in operating reserves, while the new CLPSH provides operational flexibility in power.

Regarding contributions to adequacy, energy storage capacity is the most critical parameter for ESS technology. However, in the *Dunkelflaute*, the contribution of batteries to adequacy is positively

impacted while in water inflow scenarios it remains constant. In the absence of VRES, the volume of operating reserves to be supplied decreases and batteries become more available to provide adequacy in critical hours.

The next relevant step would be to analyse the economic side of adequacy and flexibility. Given that some technologies cannot provide both, providing adequacy could sometimes penalise contributions to operational flexibility. Combining the approach presented here with the careful modelling of different flexibility services within an operation planning model would enable the economic value of the other services provided by technologies to be ascertained.

CRedit authorship contribution statement

Sébastien Huclin: Investigation, Conceptualization, Methodology, Modelling, Writing. **Andrés Ramos:** Conceptualization, Methodology, Modelling, Validation. **José Pablo Chaves:** Supervision, Conceptualization, Methodology, Writing. **Javier Matanza:** Software, Visualization, Writing. **Mikel González-Eguino:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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