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A note on flexible hydropower and security of supply: Spain beyond 2020

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ABSTRACT

Generation adequacy is a key ingredient to security of electricity supply (SoS). Some national plans envisage a future decrease in the number of coal-fired stations and an increase in renewable installed capacity. This forecast, along with the future reduction of nuclear capacity, will lead to a combination of less baseload plants and sizeable intermittent generation. Hence there is a risk that supply will be unable to meet demand and generation adequacy will suffer.

We assess how the flexible management of hydro resources can alleviate this risk by adjusting power generation to peak demand. Indeed there is empirical evidence that they are positively correlated. We compute this correlation in the case of Spain (an 'electric island'). Besides, hydro plants operate in combination with other non-dispatchable technologies within the system. Therefore, we also take their hourly seasonality into account. Next we run a Monte Carlo simulation to derive the risk profile of several adequacy metrics in the coming decades. Our results show that flexible hydro generation certainly mitigates the risk but is insufficient to bring an adecuate level of SoS when the enhanced renewable capacity goes hand in hand with a decreased baseload capacity. The risk further decreases after accounting for seasonal non-dispatchable generation, yet it still looms large. These results can be important for policy makers, system operators, and power companies when analizing investments in renewable energy with a long lifespan.

Keywords: security of electricity supply, generation adequacy, hydro stations, uncertainty, Monte Carlo, lost load.

1 INTRODUCTION

As the overall demand for electricity is anticipated to increase in the future, security of electricity supply (henceforth SoS) is eliciting ever more attention from all the stakeholders involved. It seems fair to claim that there is hardly a widely accepted definition of SoS. Nonetheless, a common thread arises from the different versions, namely the ability of power supply to meet effective demand on a continuous basis. In a sense this is a 'narrow' definition since power demand and supply do not operate in a vacuum. [1] goes beyond it by encompassing also environmental and societal concerns. This makes sense because SoS is affected by a number of factors, among them technology, markets, politics, and the environment.

The power supply in particular is a complex chain that is naturally exposed to a number of risks and uncertainties. As a demarcation criterion, the probabilities and/or impacts of the former can be more reliably computed than those of the latter. Sources of uncertainty are typically adressed by means of scenario analysis. Instead, regarding risks, the standard practice is to define and compute a number of risk metrics. This said, supply is only 50 percent of the story. [2] defines system adequacy as the existence within a system of sufficient generation and transmission capacity to meet the load, whether under normal or unusual conditions. It subsequently introduces different approaches to measure adequacy and a list of related metrics.

[3] develop a stochastic model that explicitly matches power demand and supply (if possible). From this interplay it is possible to assess generation adequacy by means of several metrics that account for different attributes of potential supply shortfalls. Next they demonstrate the model by example.

Specifically, they look at Spain (an 'electric island' right now and in the near future at least) beyond the year 2020. Monte Carlo (MC) simulation allows them derive the risk profile of several key variables. Taken together they characterize the risk profile to SoS in great detail.

In the end, [3] simulate the performance of the Spanish peninsular generating system under ten different scenarios. Regarding the installed generation capacities from 2020 through 2050, they basically draw on [4]. Importantly, [3] assume that coal-fired and nuclear stations are kept constant from 2017 to 2020 but decrease significantly in 2030 and completely cease to operate from 2040 onwards; natural gas plants, instead, are assumed to remain constant at their 2017 level through 2050. Unlike thermal stations, renewable power technologies grow in all of the scenarios, be it either slower or faster depending on the growth of power demand (either 1.36% or 1.72%). According to their results [3], the system's adequacy worsens in 2020 and does so dramatically in 2040 and 2050, when coal and nuclear stations are completely replaced by renewable plants.

The earlier results in [3] consider all power technologies as feeding their potential output in the system irrespective of demand; this general rule applies to hydro power in particular too. Because of the earth's gravitational field there is energy stored in the water that flows in rivers from upstream regions toward the sea. So-called diversion or run-of-river hydropower refers to extracting a portion of the energy contained in flowing water itself to produce electricity. Another possibility is to use the potential energy contained by a dam structure for the same purpose; this is frequently called impoundment hydropower; [5]. Importantly, this type of facilities can regulate the flow to be turbined at any precise time. Despite the differences between both types, [3] consider all hydropower plants (HPPs) as a whole. Thus, the results in [3] take monthly seasonality of hydro's load factor into account, but there is no room for strategic management of hydro plants (i.e. no aim at maximizing profits by producing more electricity at demand peaks within the month).[1] By no means this is exclusive of [3]; indeed it seems to be the usual practice. For example, [2] presents the findings from an empirical analysis on adequacy metrics and standards adopted in Europe. From the research conducted via public sources, one of the general conclusions drawn reads as follows: "*In no case was it mentioned how the operation of hydropower plants with reservoirs is considered. In countries with medium or high participation of hydropower in the generation mix, this factor is crucial for system security. In fact, in some of these countries, a dry year may be the most stressful situation in relation to generation adequacy. The use of historical series of generation data would ignore the possibility of operating reservoirs in a conservative manner, in order to increase generation adequacy (or equivalently, to reduce the risk of load shedding)*". In view of this, the EC urges to consider at least the probabilistic characterization of a number of factors, among them: "*Hydroelectric energy availability depends on the reservoir operation strategies established by the owners of plants*".

Hydropower plants with reservoirs can in principle serve several purposes, for example irrigation needs or flooding control. HPPs can be managed as SoS devices also. They are normally designed for generation during peak hours.[2] Further, some HPPs are equipped with reversible turbines or separate generating and pumping equipment (so-called pumped storage hydropower).[3] They enable the system to pump water (using electricity) from a lower reservoir up to a higher one when power demand (and presumably price) is low; when demand (price) increases, the flow is reversed. This 'load leveling' is a widespread type of load management; [7]. 'Ramping and load following' are other types of load

[1] Note that deciding when it will be more profitable to produce electricity is no easy task. At one level, suppliers draw on limited hydro energy resources available. On the other hand, future inflows are uncertain and there is a risk of spillage. According to [6], generators try to hedge against risk and are usually conservative. For example, they generally opt for deploying limited water resources when prices are moderately high, instead of waiting for a possible (uncertain) scarcity of generating resources (when the peak price would be very high) in the future.

[2] The flexibility of hydro reservoirs is often seen as the perfect complement to a system dominated by intermittent renewable sources; [7], [8]. [9] and [10] even claim that a system based on only wind, water and solar power could serve 100% of energy purposes by 2050 in a reliable and affordable way. However, this claim has received various critiques, e.g. that these authors are too optimistic about the balancing role of hydropower [11].

[3] Pumped hydro storage is the major energy storage technology. It accounts for 96% of the world storage capacity [9]; compressed air, batteries, thermal and flywheel energy storage play very minor roles. [7] and [12] highlight some of its applications (along with some barriers to its development), such as offsetting the intermittence of renewable sources and providing ancillary services to the power system (e.g. voltage regulation).

management, in which energy storage is used to assist generation to follow the load changes. In this regard, [13] point out that the business case for price arbitrage has vanished partly owing to the injection of subsidized renewable electricity during peak demand periods. To avoid becoming uneconomic, pumped storage stations have to find additional sources of revenue. [14] consider the Austrian-German spot power market and the Austrian balancing energy market through the years 2012-2015. They find that earnings from the latter may exceed those from the former many times over.

The empirical evidence shows that hydro operation does follow demand to some extent. Specifically, these stations generate relatively more power during peak hours and less in non-peak ones. On the other hand, these plants operate alongside other (non-dispatchable) technologies in a system. For example, wind energy blows during the night, when power demand is relatively lower; pump stations can avoid wasting this energy by storing it. Consequently, a detailed analysis of the contribution of hydropower to SoS calls for taking due consideration of non-dispatchable sources.[4] This note is an extension of [3] on at least three accounts. First, it aims to account for that positive correlation between maximum hourly demand and hydropower generation to check the potential of flexible management to reinforce SoS. Second, we disaggregate hydro stations between run-of-river (RoR) stations and the remainder (non-RoR) stations.; this way we want to account for the different degree of freedom between the two types when it comes to flexible management. Third, we also consider the hourly seasonality in generation from non-dispatchable technologies during peak hours. In addition, for these three reasons, now the numerical application (via MC simulation) gets more complex than in [3]. Thus, relative to [3], this paper contributes in scope, method, and policy implications. To our knowledge, no other paper on applied SoS adequacy metrics addresses the role of hydro-based generation in mitigating power supply shortfalls or the potential of seasonal non-dispatchable generation in meeting peak demands (let alone in the way we do).

In 2017 hydro stations (including pumped storage) represented about 20% of the total capacity installed in the Spanish mainland system (20,331 MW out of 99,311 MW); in terms of power generation, they provided around 8.3% of the total. Would the flexibility of hydropower alleviate estimates of supply shortages in [3]? How effective is it in enhancing SoS in mainland Spain? In the same vein, does consideration of seasonal non-dispatchable generation contribute to quell SoS concerns? If so, to what extent? According to our results, the positive correlation between hourly peak demand and flexible hydropower's generation significantly tempers the severity of the negative impacts of demand surges. The situation further improves when hourly seasonality of non-dispatchable generation is considered. Nonetheless, the expected energy not served (*EENS*) jumps above historical levels in 2030 and runs into the tens of thousands megawatts-hour thereafter. The issue is of interest not only to Spanish consumers and utilities, but also to other stakeholders involved in the construction of the European internal power market. Further, climate change might exacerbate the high variability that characterizes renewable energy sources in general and hydro power generation in particular; [15].

The remainder of the paper is organized as follows. Section 2 extends the model in [3] to account for the flexible operation of hydropower stations in mainland Spain and also the seasonal pattern of renewable generation. The resulting impact on the adequacy metrics is analyzed in Section 3. Section 4 concludes.

2 ACCOUNTING FOR HYDROPOWER FLEXIBILITY AND SEASONAL NON-DISPATCHABLE GENERATION

2.1. Model extension

[3] propose a model for evaluating generation adequacy in the long run from the viewpoint of the facilities installed. Even though power demand can be relatively predictable at this time scale, unexpected peak loads can certainly occur also in the short run; [16].

Given their focus on generation adequacy they naturally pay special attention to peak demand. Typically demand surges are short lived. Publicly available records on power demand stretch back over

[4] We thank an anonymous reviewer for bringing this issue to our attention.

many years, even decades. Unfortunately, however, their sample data on peak demand are very limited. They resort to an indirect approach that relies on yearly data; specifically, they relate the hourly peak demand in a future year ($\tilde{q}$, in MWh) to the annual demand in that year ($\tilde{Q}$, in MWh):

$$\ln\tilde{q} = \alpha + \beta \times \ln\tilde{Q} + \tilde{e}; \tag{1}$$

$\tilde{e}$ stands for an independent and identically distributed random shock. By assumption, the natural logarithm of maximum hourly demand every year follows a Normal distribution with average $\alpha + \beta \times \mathrm{E}[\ln Q]$ (where E denotes the mathematical expectation operator) and standard deviation equal to the standard error of the regression. This is a stochastic equation: though the average growth rate of $\tilde{q}$ depends on the average growth rate of $\tilde{Q}$, by its very nature $\tilde{q}$ will grow above it some times, and below it some others.

Regarding power supply, they distinguish two groups of generation technologies. The first group comprises thermal technologies: coal (c) , natural gas (g), and nuclear (n). Each station has a particular installed capacity (MW) and availability rate (%). Availability is represented by a binary variable (A). A particular station i of type $j \in \{c, g, n\}$ is in service for a fraction Λ_j^i of the year (it can either actually run or remain idle depending on power demand); it is out of service for another fraction 1-Λ_j^i (because of failures and maintenance works)*:*

$$A_j^i = \begin{cases} 0, 'off' \text{state with probability } 1 - \Lambda_j^i \\ 1, 'on' \text{ state with probability } \Lambda_j^i \end{cases}. \tag{2}$$

The second group of generation technologies includes hydro, wind, solar (both photovoltaic and thermal), cogeneration, and others. The time series of power produced/consumed by these stations subsumes both the usual pattern of failures and their intermittent nature. Consequently, [3] adopt the load factor for describing these intermittent technologies and assume that these show a stochastic behavior with both the monthly average and the volatility changing from one month to another.[5] They adopt the Weibull distribution to describe this variable across all of the technologies in this group.[6] The probability density function of the load factor (x) is:

$$f(x) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k} & \text{if} \quad x \geq 0 \\ 0 \quad \text{if} \quad x < 0 \end{cases}, \tag{3}$$

where $\lambda \in (0, +\infty)$ is the scale parameter and $k \in (0, +\infty)$ is the shape parameter. The cumulative density function is:

$$F(x) = \begin{cases} 1 - e^{-\left(\frac{x}{\lambda}\right)^k} & \text{if} \quad x \geq 0 \\ 0 \quad \text{if} \quad x < 0 \end{cases}. \tag{4}$$

The average and the variance are given by:

$$\mu = \lambda\Gamma\left(1 + \frac{1}{k}\right), \tag{5}$$

$$\sigma^2 = \lambda^2\left[\Gamma\left(1 + \frac{2}{k}\right) - \left(\Gamma\left(1 + \frac{1}{k}\right)\right)^2\right], \tag{6}$$

where Γ denotes the gamma function.

This pattern for the generation technologies in the second group applies to hydropower generation. In this sense, Eqs. (3)-(6) may be a reasonable approach as long as [3] consider hydro generation as a single power source or technology. Nonetheless, unlike [3], here we are going to disaggregate hydro stations between RoR stations and non-RoR stations. The former are relatively more dependent on natural (re)charge and less amenable to strategic management. Consequently, we are going to estimate an independent Weibull distribution for RoR stations according to Eqs. (3)-(4). Hence we can get numerical estimates of the average (μ_R) and the variance (σ_R) following Eqs. (5)-(6); the subindex *R* refers to these particular stations. Non-RoR stations include conventional reservoirs (of seasonal, annual or pluriannual regulation) and pumped storage stations (of daily, weekly or seasonal cycle). In principle they are more amenable to strategic operation and lend themselves more easily to track demand surges. Again, we assume that the load factor of these stations can be characterized by a Weibull distribution, Eqs. (3)-(4), with

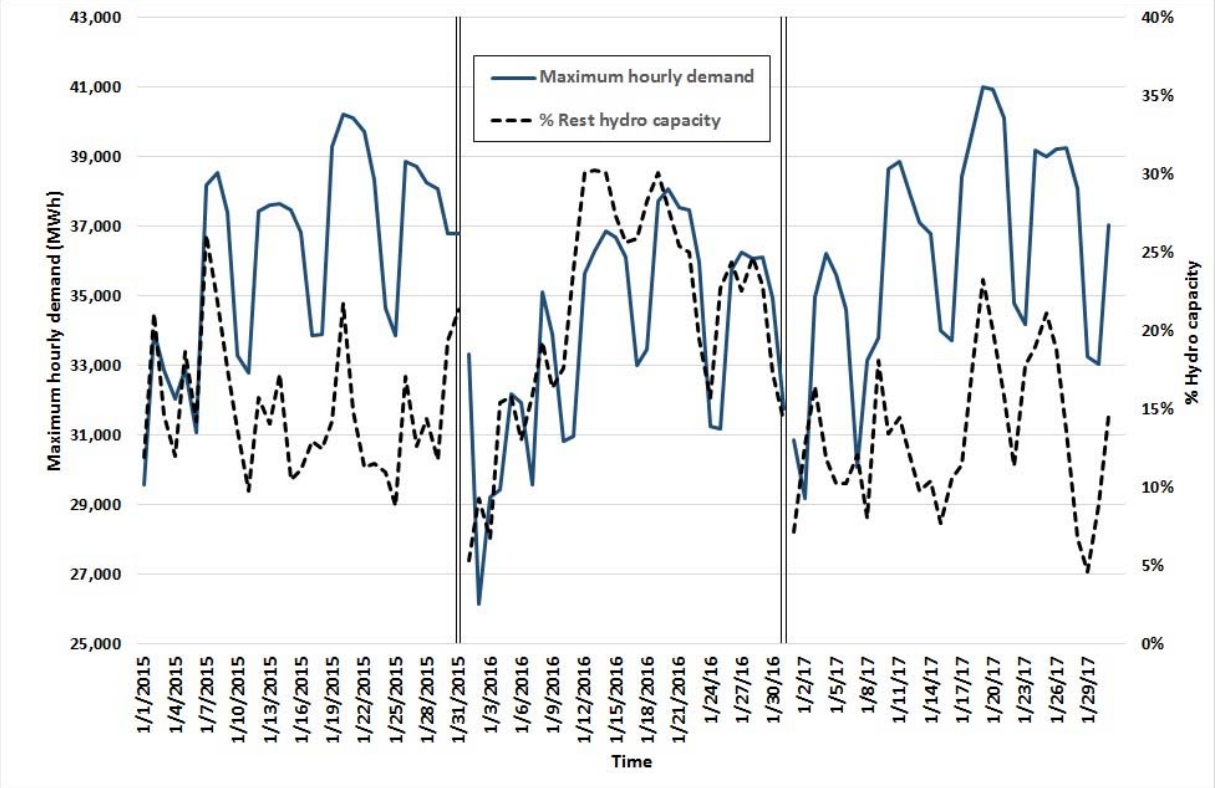
[5] Multiplying the load factor times the installed capacity allows derive samples of monthly power generation later on.

[6] Note that the Weibull distribution does not admit negative values, which is just right when dealing with load factors.

associated average (μ_P) and (σ_P) according to Eqs. (5)-(6); we adopt the subindex *P* for these hydro plants. Unlike RoR, however, the Weibull distribution for non-RoR stations is going to be correlated with peak demand.

Now the information available differs from data in [3] in three key respects: (a) we know the maximum hourly demand in each single day of the years 2015, 2016, and 2017, i.e. we have 365+366+365 = 1,096 data; (b) we know hydro-based power generation during the hours of peak demand over those years; (c) we also have hydro-based installed capacity every day (from linear interpolation between monthly values); the combined information of (b) and (c) allows computing this technology's load factor on a daily basis. Figure 1 displays the time path of hourly peak demand (a) along with non-RoR stations' load factor in January over the sample period. It suggests that these series are positively correlated. As a matter of fact, the correlation coefficient is 0.256 (the last column in Table 3 below shows the coefficient in the other months). In June it reaches the lowest value, close to zero. The upper bound is almost 45% and applies in March. The main driver behind this comovement is that power utilities manage these plants in an opportunistic or strategic way since peak demands are usually associated with higher prices (indeed hydro is the 'marginal' technology on the wholesale power market in many instances).

FIGURE 1: Maximum hourly demand and non-RoR stations' load factor in January 2015-2017.



Later on we will run a number of simulations (note that the main adequacy metrics in [3] draw on a probabilistic MC approach). Regarding RoR stations, to this end we will use the average (μ_R) and the variance (σ_R) estimated according to Eqs. (5)-(6). However, in the case of non-RoR stations we will need to generate correlated samples. We start by deriving two independent samples x_P^* and x_D^* of non-RoR stations' load factor and hourly peak demand (note the subindex *D*). In a second step we normalise each

series by subtracting its average and dividing by its volatility. Thus we obtain two independent, normalised samples x_{P} and x_{D} of the load factor and peak demand, respectively. In a third step we construct correlated samples, v_D and v_P, according to the scheme:

$$v_D = x_D; v_P = x_D\rho + x_P\sqrt{1-\rho^2}, \tag{7}$$

where ρ stands for the correlation coefficient between the two daily series.

2.2. Parameter estimation in addressing correlation

Our sample data include daily power generation and installed capacity for the two types of hydro stations. Data on these variables (b) and (c) allow computing separate, specific load factors on a daily basis. Next we arrange all of the daily load factors by month. Thus, there are 31+31+31=93 daily factors in January, 28+29+28=85 factors in February, and so on. With the daily factors in any single month we estimate a Weibull distribution for that particular month, i.e. we estimate the scale (λ) and shape (k) parameters for every month.

2.2.1. Run-of-river stations

The left block in Table 1 shows the monthly estimates of the Weibull parameters for RoR stations along with their 95 percent confidence intervals. For the scale parameter (λ) the intervals are rather narrow. The difference between the upper and lower bounds is minimum in March (4.07%) and maximum in May (10.7%). Instead, the intervals are wider for the shape parameter (k). The difference ranges between 33.1% (October) and 40.2% (January).

The next step is to substitute the monthly values of λ and k in Eqs. (5)-(6) to compute the monthly average and standard deviation of RoR stations' load factor; see the right block in Table 1. Looking at μ_R, the mean is highest in March; henceforth it declines consistently until October and then rises. Similarly, the highest volatility σ_R is reached in April and the lowest one in September. Therefore, through the three sample years, the extreme values of the mean and the volatility are rather contemporaneous. The maximum generation takes place from February to May. In 2017 the installed capacity of RoR stations was 2,104 MW [17]; see Table A1 in the Appendix.

Table 1. Run-of-River (RoR) load factor: Parameter estimates (daily data 2015-17).

Month	*Scale (λ)*		*Shape (k)*		*Average*	*Volatility*
	Value	*95% int.*	*Value*	*95% int.*	μ_R	σ_R
January	0.520	0.499—0.542	5.163	4.360—6.114	0.479	0.106
February	0.668	0.651—0.684	9.178	7.766—10.846	0.633	0.083
March	0.734	0.717—0.751	9.330	8.019—10.854	0.696	0.089
April	0.715	0.680—0.750	4.424	3.767—5.195	0.652	0.167
May	0.659	0.626—0.693	4.241	3.624—4.961	0.599	0.160
June	0.531	0.507—0.555	4.825	4.153—5.606	0.486	0.115
July	0.412	0.398—0.426	6.364	5.482—7.386	0.384	0.070
August	0.358	0.347—0.370	6.680	5.759—7.747	0.335	0.059
September	0.303	0.293—0.313	6.418	5.500—7.487	0.282	0.051
October	0.270	0.258—0.281	4.962	4.301—5.723	0.248	0.057
November	0.369	0.351—0.387	4.457	3.802—5.224	0.337	0.086
December	0.407	0.390—0.424	5.156	4.454—5.968	0.375	0.083

2.2.2. Non-RoR stations

For the rest of hydro (non-RoR) stations, as stated earlier, we assume that the Weibull distribution describing their load factor is correlated with peak demand; see Figure 1. In 2017 the capacity installed amounted to 18,227 MW; see Table A1 in the Appendix. We display the Weibull parameter estimates in Table 2. Again, the confidence intervals are thinner for the scale parameter than for the shape parameter.

Hence we further compute the average and the volatility of the load factor (μ_P, σ_P) by means of Eqs. (5)-(6).

Table 2. Rest of hydro (non-RoR) load factor: Parameter estimates (daily data 2015-17).						
Month	*Scale (λ)*		*Shape (k)*		*Average*	*Volatility*
	Value	*95% int.*	*Value*	*95% int.*	μ_P	σ_P
January	0.406	0.385—0.427	4.113	3.513—4.813	0.368	0.101
February	0.447	0.421—0.475	3.692	3.080—4.425	0.404	0.122
March	0.470	0.448—0.492	4.584	3.903—5.383	0.430	0.107
April	0.374	0.343—0.406	2.585	2.198—3.039	0.332	0.138
May	0.355	0.325—0.386	2.492	2.117—2.933	0.315	0.135
June	0.285	0.264—0.306	2.951	2.500—3.483	0.254	0.094
July	0.251	0.230—0.272	2.535	2.153—2.982	0.223	0.094
August	0.225	0.208—0.243	2.837	2.418—3.327	0.201	0.077
September	0.222	0.207—0.237	3.146	2.678—3.694	0.199	0.069
October	0.252	0.232—0.271	2.758	2.336—3.256	0.224	0.088
November	0.262	0.239—0.288	2.343	1.981—2.770	0.233	0.105
December	0.266	0.244—0.289	2.598	2.202—3.065	0.236	0.098

Table 3 shows the descriptive statistics of hourly peak demand and further information about the correlation with power generation form non-RoR stations.[7] The latter sheds light on the statistical significance and accuracy of the monthly estimates. We start from the standard (Pearson) formula (thus assuming a linear relationship between both variables). As a safeguard against sampling error we conduct a test. The null hypothesis is $\rho = 0$. The alternative hypothesis is $\rho \neq 0$ (which requires a two-tail test). The ***t***-test for the correlation observed is:

$$t = \frac{\rho\sqrt{n-2}}{\sqrt{1-\rho^2}}, \tag{8}$$

where ***n*** stands for the number of observations; this ***t***-test has ***n***-2 degrees of freedom. As for the confidence interval we first turn the observed correlation into Fisher's transform:

$$z' = \frac{1}{2} ln \frac{1+\rho}{1-\rho}. \tag{9}$$

Hence the interval for the ***z'*** transform is computed as:

$$IC(z') = \left[z' - 1.96\frac{1}{\sqrt{n-3}}; z' + 1.96\frac{1}{\sqrt{n-3}}\right]. \tag{10}$$

And the resulting interval for the correlation observed is calculated as:

$$IC(\rho) = \left[\frac{\exp\left(2\left(z' - \frac{1.96}{\sqrt{n-3}}\right)\right)-1}{\exp\left(2\left(z' - \frac{1.96}{\sqrt{n-3}}\right)\right)+1}; \frac{\exp\left(2\left(z' + \frac{1.96}{\sqrt{n-3}}\right)\right)-1}{\exp\left(2\left(z' + \frac{1.96}{\sqrt{n-3}}\right)\right)+1}\right]. \tag{11}$$

The information above allows assess the rosbustness of our numerical estimates.

Table 3. Basic statistics of hourly peak demand and correlation with non-RoR's load factor.						
	Hourly peak demand		*Correlation Coefficient*			
Month	μ_D	σ_D	# Obs.	ρ	*p*-value	*95% conf. int.*
January	35,424	3,207	93	0.256	0.0132	0.055—0.437
February	35,280	2,528	85	0.381	0.0003	0.183—0.550

[7] We thank an anonymous referee for raising this point.

March	33,340	2,563	93	0.449	0.0000	0.270—0.598
April	30,715	2,338	90	0.326	0.0017	0.128—0.499
May	30,572	2,251	93	0.101	0.3364	-0.105—0.299
June	33,048	2,953	90	-0.012	0.9115	-0.219—0.196
July	35,290	3,158	93	0.369	0.0003	0.179—0.533
August	33,186	2,954	93	0.215	0.0382	0.012—0.401
September	32,236	2,766	90	0.194	0.0674	-0.014—0.386
October	31,087	2,335	93	0.179	0.0869	-0.026—0.369
November	33,174	2,903	90	0.152	0.1514	-0.057—0.348
December	33,654	2,998	93	0.101	0.3370	-0.105—0.299

We are going to simulate a Weibull distribution 50,000 times each month using the parameter values of λ and k and then compute the average load factor and its volatility. Provided the latter closely mirror those derived from our sample data, the numerical estimates of the MC-based adequacy metrics can be considered reliable. Table A2 in the Appendix shows the results from both the sample data and the simulation runs in each month. The (negligible) differences observed can be attributed to the limited number of runs and the very nature of random numbers.

Regarding the maximum hourly demand, we resort to Eq.(1). As in [3], we take random samples for the shock term and shift the maximum demand curve in 2017 accordingly. Specifically we use 50,000 simulation runs (i.e. years, each comprising 365 days). We group them by month and compute the monthly average and volatility, μ_D and σ_D, respectively; see the left block columns in Table 3. Peak demand surges typically in January (35,424 MWh) and July (35,290); these months are also the most volatile ones (3,207 MWh and 3,158, respectively).

The right block in Table 3 proves the importance of extending [3] along the lines drawn in this note. To begin with, at the yearly level (i.e. neglecting differences across months) the correlation between non-RoR stations' load factor and hourly peak demand is 0.214 (statistically different from zero at the 5% confidence level). The analysis on a monthly basis shows that, for most of the year, there is a mild correlation. It ranges from about 0 to 25% in eight out of twelve months, slightly alleviating power supply shortages (the computation draws on all the daily values of both variables in any single month). Nonetheless, the flexibility advantage of hydropower gets larger in months with a high load factor (January to April), with the correlation coefficient rising up to 45%; this suggests that higher water levels in reservoirs do allow a more flexible and strategic management of those reservoirs; [18], [19]. Just half of the monthly estimates of ρ are statistically different from zero (again, at the 5% confidence level). Interestingly, they are significant from January to April along with July and August, precisely the months when the coefficient reaches its highest values. This said, we can also observe that the confidence intervals are wide, the upper bound being several times higher than the lower one on many occasions. This confirms the usefulness of accounting for the seasonal behavior of the correlation between non-RoR's load factor and peak demand, and of using monthly parameters in this analysis.

Monthly differences in correlation can be traced back to several issues.[8] On the supply side, within non-RoR stations there are HPPs with reservoirs (installed capacity 11,900 MW) and pumped storage stations (6,327 MW). Spain has 20 pumped storage plants.[9] They were commissioned through the 20th century mainly to address rainfall variability. So-called Hydrographic Confederations rule the basins; they are legally above hydropower operators since they set limits on the use of water. From this perspective, somehow there is an upper bound on power generation from non-RoR stations which is affected by both

[8] We thank an anonymous referee once more for bringing this issue to our attention.

[9] They can be further subdivided into two types: pure or closed-loop (where water is first pumped to an upper reservoir and then released to generate power) and mixed or open-loop (when there are water contributions from rivers). Pure pumped storage accounts for 53% of the total (3,337 MW) while mixed pumped storage takes the remaining 47%.

actual rainfall and water needs. The so-called '*hydropower potential*' measures the maximum amount of electricity that could be theoretically produced from the water contributions during a particular period of time after subtracting the water diverted for irrigation or other uses different from power generation. Table A3 and Figure A1 in the Appendix show that the highest hydropower potentials are available during the first three or four months of the year. They subsequently decline through summer and start rising in autumn.

At the same time, power demand also plays a role here; it changes seasonally over time (Table A3 and Figure A1 in the Appendix). The average peak demand in particular is highest in January and July (Table 3) followed by February (which lags close behind, with 35,280 MWh). In general, the first months of the year tend to be also the months when the correlation between peak demand and hydro's load factor is relatively higher (as shown in Table 3); this also applies to July (maybe in an effort to make ends meet).

Anyway, a cautionary note seems in order.Water reserves at the end of 2017 were at their lowest level on record (starting 1990); [20]. Hydro-based generation decreased almost in half with respect to 2016, and reached its lowest value since 2005. Hydro was the third power generation source in 2016 but dropped to the sixth in 2017. The drought in 2017 dragged renewable generation down from 40.3% of total in 2016 to 33.7% in 2017. This episode attests to the high variability of renewable resources, both at yearly and monthly levels (for one, hydro-based generation contributed 26% of total power in May 2016 but 10.1% in May 2017, its lowest level on record).

Annual variability certainly complicates drawing conclusions from just three years of observations. Yet a fact speaks for itself: in 2017 the average contribution of pure pumped storage to power generation was just 0.9%; nonetheless, it jumped to 6.7% in the day of peak demand (January 25th); [20]. This fact highlights its role in addressing SoS concerns.

2.3. Parameter estimation in addressing seasonality

Our initial model does not account for any hourly seasonality. Note, however, that we do not use the 24 hourly demands in any single day, but only the maximum hourly demand in that day. We proceed as follows.

We consider the twelve months of 2017, our base year. Every day in every month has a maximum hourly demand at a particular time. We take each month in isolation and identify the most frequent hour at which the maximum hourly demand takes place. Thus, in the case of January, the typical hour with maximum demand is 21:00; instead, in July it is 14:00.

We have hourly power generation by all of the non-dispatchable technologies other than non-RoR (i.e. RoR, wind, solar, cogeneration, and others) from 2015 through 2018, i.e. four years. Now, let's think of a particular renewable technology, say wind, and a particular month, say January. There are four such months in the sample, each running from day 1 to day 31. We thus have 4×31= 124 January days; we adopt the sub-index k for each one of them, with k =1, 2,…, 124. On the other hand, each day comprises 24 hours, denoted by sub-index i, with i =1, 2,…, 24. Therefore, we have 142 observations for hour 1 in January, another 142 observations for hour 2 in January, 142 observations for hour 3 in January, and so on until hour 24 in January.

Initially we compute the hourly average generation in each day (μ_k) summing up its 24 hourly levels and then dividing by 24. Next, we divide each of these 24 hourly levels in day k by the hourly average that day (μ_k) just calculated. This way we derive a series of seasonal factors for each hour, with each series comprising 124 terms. We denote each factor by φ_{ik} (again, with i =1, 2,…, 24 and k =1, 2,…, 124). Drawing on the 124 values for hour i, the i-th seasonal factor for wind in January is just their average:

$$\varphi_i = \frac{1}{124}\sum_{k=1}^{124} \varphi_{i,k}\,, where \;\; i = 1,2,\dots,24. \tag{12}$$

Thus we get a series of 24 factors (φ_i, with i=1, 2,…24), one for each hour of the day in Januaries; they can be interpreted as representing hourly seasonality (in generation from wind). Some of them are higher than 1, and some others are lower than 1; they sum to 24:

$$\sum_{i=1}^{24} \varphi_i = 24. \tag{13}$$

Henceforth, we follow this procedure: we simulate the daily average generation in any single January day from wind (μ). Then we use the above factors φ_i (based on empirical/historical evidence) to

account for the hourly variability in generation from wind (note that they in turn depend on the empirical averages μ_k). Specifically, since we have 24 factors φ_i, we compute 24 hourly generation levels from wind in that January day. This way we hope to address the issue raised by the Reviewer (as we interpret it: potential seasonalities at the hourly level).

Needless to say, the same procedure is applied every other month, from February to December. It is also applied across non-dispatchable technologies. The only exception is non-RoR, whose hourly seasonality was already taken into account through its correlation with hourly peak demand. The aim is to compare the ensuing results with those when seasonality is left aside.

Table 4 below shows the most frequent hour of maximum demand in each month. Power demand reaches its hourly maximum around 21:00 in seven months. The other months, instead, the maximum is reached around 14:00. Table 4 also displays the factor φ_i that applies to each non-dispatchable technology in that particular hour. A value above 1.0 means that the technology is operating "above daily average" at that precise time (e.g. wind at 21:00 in January); a value below 1.0 means the opposite (e.g. solar at 21:00 in January).

TABLE 4. Seasonal factors of power generation from renewable technologies in peak-demand hours.

Month	Hour	Wind	Solar	Cogen.	Others	RoR	Non-RoR
January	21:00	1.0340	0.0944	1.0222	1.0239	1.1139	1.8184
February	21:00	1.0548	0.1386	1.0244	1.0268	1.0866	1.6418
March	21:00	1.0512	0.2592	1.0171	1.0198	1.0663	1.5909
April	22:00	1.1077	0.2443	1.0190	1.0210	1.0539	1.5965
May	13:00	0.8423	2.2985	0.9981	1.0007	1.0342	1.2429
June	14:00	0.7797	2.2280	0.9921	0.9951	1.0577	1.4104
July	14:00	0.7297	2.1776	0.9933	0.9969	1.1121	1.5841
August	14:00	0.7389	2.4004	0.9962	0.9978	1.1165	1.5479
September	14:00	0.7468	2.6408	0.9960	0.9983	1.0737	1.2829
October	21:00	1.0779	0.2027	1.0090	1.0117	1.1255	2.2618
November	21:00	1.0330	0.0932	1.0089	1.0135	1.1290	1.9737
December	21:00	1.0162	0.0758	1.0072	1.0119	1.1241	1.9565

Note: A factor above (respectively, below) 1.0 means power generation above (resp., below.) daily average.

3 FLEXIBILITY, SEASONALITY, AND ADEQUACY METRICS

Here we assess the impacts of both factors on the adequacy metrics for mainland Spain and how they compare to the results in [3]. We do it sequentially: we start considering flexibility in isolation, and then we add seasonal non-dispatchable generation on top of it.

3.1. Flexible hydropower

First, we illustrate how the flexible management of hydro stations alleviates supply shortages in mainland Spain. Regarding power demand, as explained in [3], maximum hourly demand in a year is regressed on yearly demand as shown in Eq. (1) from 1990 through 2017. The ordinary least squares regression analysis yields α= -7.24270 (t-ratio = -10.82), β= 0.924459 (t-ratio = 26.45), and adjusted R-squared of 0.976980; the standard error of the regression is 0.034453. Hence, starting from the demand level in 2017 and assuming both a particular growth rate (e.g. 1.36%) and number of years ahead (say, 13) we can derive a forecast for total demand in, say, the year 2030. Substituting the resulting level in the regression equation we derive the (log) average peak demand in that year. Next we can simulate the maximum hourly demand in each day of the year 2030 in mainland Spain. Any particular simulation run (out of 50,000) yields a particular peak demand in that year. We compute the difference between this simulated peak demand and the actual peak demand in 2017. In order to get the hourly peak demand in 2030

on a daily basis we shift vertically the whole demand curve in 2017 downwards/upwards by this amount.

As for mainland power supply, Table A1 in the Appendix shows the generation mix by technology at year-end 2017. It is exactly the same as in [3]. The only difference is that now we separate hydro capacity between RoR and non-RoR technologies. Specifically, RoR capacity is assumed to remain constant through the time horizon considered (up to 2050) at 2,104 MW. Instead, non-RoR capacity starts from 18,227 MW in 2017 and grows more or less over time according to the assumed yearly growth of power demand (whether 1.36% or 1.73%). Regarding thermal plants, we perform 50,000 simulation runs of their available capacity in each month. As for non-thermal technologies, we derive 50,000 random samples of their load factor in each month; the two types of hydro stations are considered separately (just like any other technology). Then we compute the combined power generation from both thermal and non-thermal stations. The resulting level is multiplied by a factor of 0.9809 (the availability rate of Spanish power grid).

As already mentioned, [4] consider two scenarios of future demand growth: 1.36% and 1.73% per year. [3] stick with these two demand scenarios, denoted D_1 and D_2, respectively. Concerning supply, depending on the assumed growth rate of demand, they adopt different installed capacities for each technology in the coming decades. Thermal stations in particular show the same path in all the scenarios: coal-fired and nuclear stations remain constant from 2017 to 2020 but decrease significantly in 2030 and completely cease to operate from 2040 onwards; natural gas plants, instead, are assumed to remain constant at their 2017 level through 2050. Non-thermal power technologies undergo weaker or stronger growth according to demand growth. [3] denote these generation systems by S_1 and S_2, assumed to match demands D_1 and D_2, respectively; see Table A1 in the Appendix. In the end, [3] simulate the performance of the Spanish peninsular generating system in ten different scenarios. After matching the earlier two parks S_1 and S_2 with demands D_1 and D_2, they are subsequently combined with a flat future demand (D). These four scenarios [(S_1,D_1), (S_2,D_2), (S_1,D), (S_2,D)] are then followed by another four in which the base demands are lowered by 5% [(S_1,D_1^-), (S_2,D_2^-), (S_1,D^-), (S_2,D^-)]. Finally, [3] take the scenarios [(S_1,D_1^-), (S_2,D_2^-)] and compare them with two other scenarios where gas-fired generation capacity is increased since 2030 through 2050, denoted [(S_1^+,D_1^-), (S_2^+,D_2^-)].

We focus on the last two spectific cases, namely [(S_1^+,D_1^-), (S_2^+,D_2^-)]. In them annual demand grows (on average) at 1.36% or 1.73% (denoted D_1 and D_2, respectively) and so does hourly peak demand (on average), but the associated hourly peak demand levels are cut by 5% if necessary from 2030 onwards; we refer to them as 'shaved' demand (D_1^- or D_2^-). At the same time, natural gas-fired generation capacity grows by 3,000 MW every decade; we refer to this as'enhanced' supply (S_1^+ or S_2^+). This corresponds to the lower block of Table 7 in [3]; the upper part of Table 5 here replicates it for convencience; it represents inflexible hydropower generation. Remember that these demand growth scenarios envisage a wide deployment of renewable sources of electricity in [3]. The middle block in Table 5, instead, displays the adequacy metrics under flexible management of hydropower.

As expected, the positive correlation between hourly peak demand and flexible hydro's load factor tempers the severity of the negative impacts of demand surges. Table 6 shows the decrease that applies to each probabilistic metrics in each year considered. For instance, in 2020 the percentage change in *EENS* with respect to inflexible management equals [(2/48) − 1] × 100 = − 95.8 % (under D_1^-) or [(3/85) − 1] × 100 = − 96.5 % (under D_2^-). This is obviously a dramatic reduction in the supply shortfall. Yet the impact fades over time as demand keeps on growing (whether at 1.36% or 1.73% per year) despite the broad deployment of renewable sources; by the end of the time horizon the drop in *EENS* is close to 60% or 55%, respectively. The same dynamics applies to the other adequacy metrics, whether we look at their average values or the 95 percentiles. Interestingly, the probability that the peak load will exceed available generation, *LOLP*, is basically unaffected in 2040 and 2050.

Table 5. Spanish peninsular system: Simulated mismatch between 'enhanced' supply and 'shaved' demand.

	2017	*2020*	*2030*	*2040*	*2050*	*2020*	*2030*	*2040*	*2050*
AD	253,082	263,621	302,026	346,026	396,436	266,564	316,909	376,762	447,920

MHD	42,398	44,013	47,365	53,661	60,801	44,463	49,502	58,023	68,023
AC	99,311	113,232	121,430	126,948	141,648	110,832	126,630	140,648	168,548
		Inflexible hydro generation (S_1^+,D_1^-)				*Inflexible hydro generation* (S_2^+,D_2^-)			
$EENS$	23	48	1,415	151,248	317,338	85	3,485	258,069	547,173
$E95$	0	0	4,814	483,212	874,788	0	21,963	736,823	1,342,998
$LOLE$	1.44	2.54	53.01	2,945.50	4,980.68	4.27	115.01	4,219.63	6,614.56
$L95$	0	0	420	7,500	10,920	0	840	9,600	12,780
$LOLP$	0.55	0.88	10.40	93.72	98.24	1.36	18.21	97.33	99.43
RM	1.34	1.57	1.56	1.37	1.33	1.49	1.56	1.42	1.48
		Flexible hydro generation (S_1^+,D_1^-)				*Flexible hydro generation* (S_2^+,D_2^-)			
$EENS$	23	2	98	46,124	124,546	3	301	92,784	247,847
$E95$	0	0	0	171,687	387,350	0	847	307,807	667,387
$LOLE$	1.44	0.10	4.80	1,218.85	2,617.18	0.21	13.12	2,046.40	3,993.92
$L95$	0	0	0	3,660	6,540	0	60	5,400	8,520
$LOLP$	0.55	0.12	3.35	92.01	98.43	0.24	7.45	97.08	99.69
RM	1.34	1.57	1.56	1.37	1.33	1.49	1.56	1.42	1.48
		Flexibility & Seasonality (S_1^+,D_1^-)				*Flexibility & Seasonality* (S_2^+,D_2^-)			
$EENS$	23	0.15	77.96	30,987	79,401	2.77	234.32	57,855	151,234
$E95$	0	0	0	125,788	265,549	0	354.16	212,929	446,637
$LOLE$	1.44	0.01	3.75	773.91	1,577	0.16	10.06	1,197	2,339
$L95$	0	0	0	2,400	4,080	0	60	3,300	5,220
$LOLP$	0.55	0.01	2.74	85.25	95.54	0.19	5.90	91.75	98.34
RM	1.34	1.57	1.56	1.37	1.33	1.49	1.56	1.42	1.48

Table 6. Percentage change in adequacy metrics induced by flexible non-RoR generation.

	Demand growth: +1.36%				Demand growth: +1.73%			
	2020	*2030*	*2040*	*2050*	*2020*	*2030*	*2040*	*2050*
$EENS$	-95.8%	-93.1%	-69.5%	-60.8%	-96.5%	-91.4%	-64.0%	-54.7%
$E95$	-	-100.0%	-64.5%	-55.7%	-	-96.1%	-58.2%	-50.3%
$LOLE$	-96.1%	-90.9%	-58.6%	-47.5%	-95.1%	-88.6%	-51.5%	-39.6%
$L95$	-	-100.0%	-51.2%	-40.1%	-	-92.9%	-43.8%	-33.3%
$LOLP$	-86.4%	-67.8%	-1.8%	0.2%	-82.4%	-59.1%	-0.3%	0.3%

In sum, the possibility of shortages still looms large in the long term and remains worrying. For one, *EENS* amounted to 23 MWh in 2017; according to our results, it falls to just 2 or 3 in 2020 but jumps to a few hundred in 2030 and runs into the hundreds of thousands afterward.

To some extent, the contribution of flexible hydropower management to SoS reflects the particular operation of pure pumped storage (PHES) plants in Spain. Figure A2 in the Appendix displays their actual operation profile over the period 2014-2018. Even though their aggregate installed capacity amounts to 3,337 MW, their usual net output is quite far from operation at full capacity. This fact may be attributed to a number of factors, such as profitability of hydro plants (see footnote 1), constraints due to reservoir volume or reservoir seasonal constraints [8].

3.2. Flexible hydropower and seasonal renewable generation

Now we assess the impact of seasonality in combination with hydropower flexibility. For this purpose, we focus on the lower block in Table 5 and compare it with the central one (flexible hydropower generation). From a cursory look it is clear that accounting for hourly seasonality does alleviate SoS

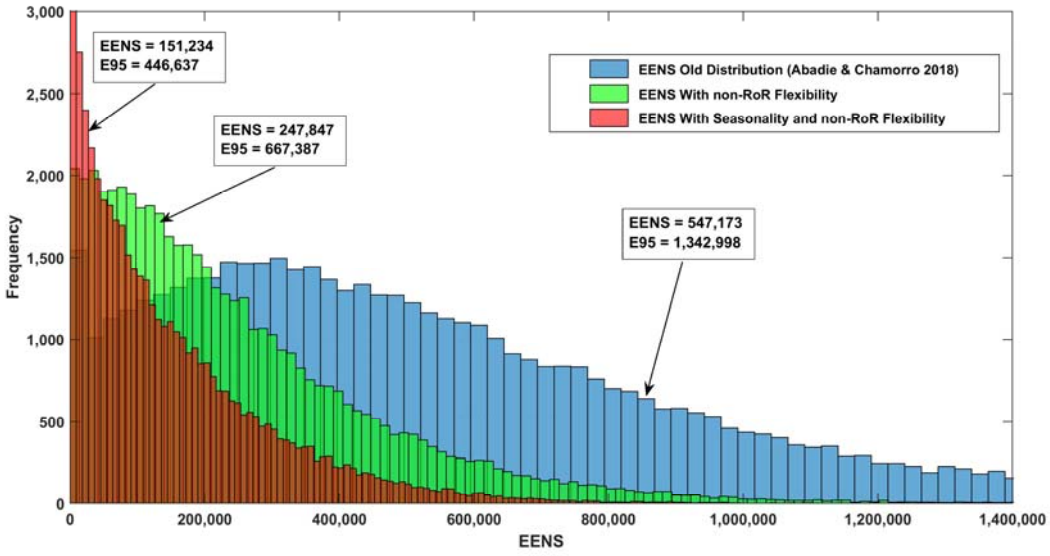
concerns. Table 7 shows that, in 2020, *EENS* drops dramatically under slow demand growth, [(0.15/2)-1]×100= -92.3%, but much less under faster growth, [(2.77/3)-1]×100= -7.8% (probably, some values close to zero in that year have an oversized impact on the percentage changes). From then on, the size of the reduction grows with the passage of time (and further deployment of renewables), ranging between 20% and 40%, which is a significant improvement. The 95th percentile (*E95*) decreases too, thus improving the severity of the shortfalls. The average number of hours in a given year with *EENS* occurrence (*LOLE*) falls a bit more then *EENS*; the same applies to its 95th percentile (*L95*) with respect to *E95*. Unlike these metrics, the probability that the peak load will exceed available generation (*LOLP*) does not drop so much; worse still, the decrease gets smaller over time, leaving *LOLP* almost unaffected by 2050.

Table 7. Percentage change in adequacy metrics induced by seasonality (except in non-RoR).

	Demand growth: +1.36%				Demand growth: +1.73%			
	2020	*2030*	*2040*	*2050*	*2020*	*2030*	*2040*	*2050*
EENS	-92.3	-20.5	-32.8	-36.2	-7.8	-22.2	-37.6	-39.0
*E*95	—	—	-26.7	-31.4	—	-58.2	-30.8	-33.1
LOLE	-88.0	-21.8	-36.5	-39.7	-22.9	-23.3	-41.5	-41.4
*L*95	—	—	-34.4	-37.6	—	0.0	-38.9	-38.7
LOLP	-88.3	-18.1	-7.3	-2.9	-22.5	-20.9	-5.5	-1.4

Figure 2 displays the probability distribution of *EENS* for the year 2050 under the second demand growth scenario (D_2^-) in the three settings: the default situation (as in [3], i.e. without taking correlation and seasonality into account), with correlation (i.e. flexible hydropower management), and with both correlation and seasonality. As we move from the first setting to the second one there is a massive displacement of the probability mass towards the left. As observed in Table 6, when hydro operators follow peak demand the *EENS* is cut almost by 55 % while its 95th percentile (*E95*) falls a bit less, about 50%. Thus, the positive correlation certainly softens the problem, but in no way solves it. Next, if we compare the initial and the final distributions, the average *EENS* drops by 72.36% and *E95* by 66.74%. Summing up, despite the huge improvement brought about by flexibility and seasonality, the risks around SoS continue to be extremely serious, both by past national standards and international ones.

FIGURE 2: Major adequacy metrics in 2050 (under high demand growth) in the three different settings.



4 CONCLUSIONS

Security of electricity supply (SoS) is a serious concern of future power generation. In a number of national systems the foreseeable development of renewable technologies and the gradual demise of nuclear and coal-fired stations can pose an added risk to security of supply. This risk can be alleviated to some extent by using the hydroelectric resources available in a flexible way. As a general rule, the power available from hydro stations depends on the operation strategies implemented by the plants' owners. In this regard, "*A conservative operation will keep a minimum volume of water stored, to ensure the energy necessary to operate at full capacity in dry years; but economic optimization may lead to less conservative operation*"; [2]. On the other hand, hydro plants operate in combination with other non-dispatchable technologies in a system. Consequently, a detailed analysis of the contribution of hydropower to SoS calls for taking non-dispatchable sources into account, in particular their seasonal pattern over short periods.

Here we develop a model to assess the performance of different, prospective generation parks from the viewpoint of SoS. We demonstrate it by application. At this point, instead of making assumptions on how hydro stations with reservoirs will be (or should optimally be) operated,[10] we draw on observed historical patterns (somehow emphasyzing, as in [3], a rather physical/technical approach). We take the correlation between hydro-based power generation and peak demand into account. Specifically, we distinguish run-of-river (RoR) stations from the remainder, non-RoR hydro stations. This way we not only account for the aforementioned correlation, but for the flexible management of pump stations as well. Thus, we can assess the potential role of each particular type of hydro technology in enhancing SoS. This point is particularly important when it comes to pump stations, since the need for additional storage capacity in the future is widely recognized (not only in Spain). On the other hand, we use hourly data whenever publicly available. In particular, every month we compute the hourly seasonality attached to each type of renewable energy; this way we get a better representation of supply from renewable sources. The observed seasonal pattern is applied to the hours of maximum demand.

Our results show that flexibly managing Spanish hydro resources sizeably reduces power shortages. Yet, by itself it may not be enough to guarantee SoS during peak hours under specific configurations of the installed generation capacity. The outlook improves to some extent when the hourly seasonality of non-dispatchable generation is also considered. In general, during peak hours non-dispatchable technologies generate power above their daily averages, thus significantly contributing to SoS. This said, although the management of existing hydropower reservoirs could still be improved, [19], [23], the magnitude of our results indicates that there may be a need for (additional) demand shedding or supply increases coupled with higher storage capacity.

As [7] point out, storage projects must be assessed in the context of a changing power sector. In this regard, most stations in Spain were built when the electricity market was tightly regulated. The current liberalized market may not provide strong enough incentives to attract new investments in this area. In early 2019 the Spanish Government released the draft of the Integrated National Plan of Energy and Climate-PNIEC [24]. It surmises an increase in the installed capacity of pure pumped stations from its current level of 3,337 MW to 4,212 by 2025 and 6,837 MW by 2030. Whether the private sector will undertake these investments remains to be seen.[11]

Besides, as of today, none of the functions legally assigned to the power system operator (Red Eléctrica de España) implies the hydro exploitation of these generating facilities; [25]. Further, Hydrographic Confederations may set more restrictive ecological flows or limits to the rate of change of the turbined flows, which could decrease flexibility and ability to use hydropower in the operation of the power

[10] [7] and [21], among others, assume that utilities have perfect foresight about the day-ahead marginal electricity price when optimizing their hydro stations. [22] assume a random price of electricity, which entails the need to account for this (price) risk.

[11] For example, [13] warn of growing concerns regarding pumped-storage technologies as 'peak assets', because of both a diminished business case for price arbitrage (induced by the integration of subsidized renewable electricity) and the competition from alternative cheaper solutions (such as gas-fired power plants).

system, and therefore could impact its security.[12] According to the PNIEC, there will be regulatory changes to the operation of pure pumped stations; they would be managed by the system operator (for example, as SoS devices). Yet, as of today this legal framework remains undeveloped.

Regarding future research, the above analysis could be improved along several lines, both methodological and empirical (assuming the required data are publicly available). For example, solar technologies could be disaggregated into photovoltaic and thermal to account for their different charge/discharge cycles; in principle, doing so would improve the accuracy of our estimates. The empirical analysis could ideally be conducted over a longer sample period to dampen the potential impact of the dry year 2017 on the results. Beyond this, the combination of solar PV and wind parks with storage facilities can improve SoS substantially by means of technologies such as pumped hydro storage (the need to additionally invest in storage, on top of the generation facilities, makes these power systems relatively expensive in general). For example, the scenarios in [27] deploy pumped hydro (with daily-weekly storage durations) due to its technological maturity and potential in the Ontario landscape. In addition to pumped storage, [28] consider also central batteries and hydrogen storage in the future European power system. Additional storage capacity can be incorporated into our model to some extent as long as it can be interpreted like a cut in peak demand hours.

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[12] [26] consider a hybrid wind/pumped-hydro system in Madeira Island (Portugal) with multiple purposes: supply water, regularize the irrigation flows, and produce electricity. They optimize the hourly operation of the pumps and turbines for a period of one day.

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Appendix

Table A1 displays the total installed capacities (in MW) of power technologies in mainland Spain and the peninsular total annual demand (in GWh). Source: [3].

Table A.1. Peninsular Spanish power system.

		S_1 (demand growth: +1.36%)				S_2 (demand growth: +1.73%)			
	2017	*2020*	*2030*	*2040*	*2050*	*2020*	*2030*	*2040*	*2050*
Nuclear	7,117	7,117	3,040	0	0	7,117	3,040	0	0
Coal	9,536	9,536	6,642	0	0	9,536	6,642	0	0
Natural Gas	24,948	24,948	24,948	24,948	24,948	24,948	24,948	24,948	24,948
Hydro:	20,331	20,331	21,900	24,700	25,600	20,331	23,300	25,900	28,600
RoR	2,104	2,104	2,104	2,104	2,104	2,104	2,104	2,104	2,104
Non-RoR	18,227	18,227	19,796	22,596	23,496	18,227	21,196	23,796	26,496
Wind	22,863	26,000	28,700	32,100	35,800	24,500	32,600	39,800	44,400
Solar	6,730	16,000	20,500	24,600	29,400	15,100	20,300	27,300	39,300
Cogen.	6,373	8,100	9,900	10,800	11,600	8,100	10,800	13,200	16,100
Others	1,413	1,200	2,800	3,800	5,300	1,200	2,000	3,500	6,200
Total(MW**)**	99,311	113,232	118,430	120,948	132,648	110,832	123,630	134,648	159,548
Demand (GWh)	253,082	263,621	302,026	346,026	396,436	266,564	316,909	376,762	447,920

Table A2 displays the basic statistics derived from our sample data of non-RoR stations (left block) and those resulting from 50,000 simulation runs (on the right). They are almost identical, which renders our MC-based adequacy metrics relatively reliable. In other words, this table basically serves as a cross-check of our non-RoR paremeters in the simulations above. For pumped-storage stations we use an availability rate of 60.66% of their installed capacity; this is the 95th percentile of the 2015-2017 daily series.

Table A2. Non-RoR: Estimated Weibull parameters and those from Monte Carlo simulation.

	Estimated			Simulated		
Month	Mean μ_P	Volatil. σ_P	ρ	Mean μ_P	Volatil. σ_P	ρ
January	0.368	0.101	0.256	0.368	0.101	0.256
February	0.404	0.122	0.381	0.404	0.122	0.382
March	0.430	0.107	0.449	0.430	0.107	0.451
April	0.332	0.138	0.326	0.332	0.138	0.326
May	0.315	0.135	0.101	0.315	0.135	0.100
June	0.254	0.094	-0.012	0.254	0.094	-0.013
July	0.223	0.094	0.369	0.223	0.094	0.368
August	0.201	0.077	0.215	0.201	0.077	0.216
September	0.199	0.069	0.194	0.199	0.069	0.193
October	0.224	0.088	0.179	0.224	0.088	0.180
November	0.233	0.105	0.152	0.232	0.105	0.153
December	0.236	0.098	0.101	0.235	0.098	0.100

Table A3 shows the maximum generation potential from hydro stations (in Spanish, '*producible hidráulico*') and power demand as an approach to explaining the factor(s) behind the monthly changing correlation between the former's load factor and the latter.

Table A3. Behind the correlation between demand and hydro's load factor.

	Hydropower potential (GWh)			Power demand (GWh)		
Month	2015	2016	2017	2015	2016	2017
January	2,612	6,024	1,124	22,694	21,470	23,109
February	4,204	4,889	3,802	21,013	20,848	19,912
March	4,133	4,603	2,667	21,184	21,477	21,128
April	2,913	6,105	1,546	18,851	19,931	18,833
May	2,576	5,483	1,990	19,832	19,732	20,242
June	1,535	2,112	1,074	20,377	20,247	21,709
July	578	915	557	23,470	22,235	22,401
August	647	367	253	20,880	21,464	21,809
September	877	470	287	19,591	20,845	20,215
October	1,503	729	411	19,728	19,852	20,252
November	1,980	1,592	528	19,880	20,663	20,950
December	1,314	1,378	1,734	20,897	21,336	22,181

Source: Red Eléctrica de España (REE).

Figure A1 displays both series from Jan 2015 to Dec 2017. Hydro potential is measured along the left vertical axis; demand goes along the right one. In both cases, monthly values represent percentages, i.e. the abosulte levels are divided by the yearly totals. For instance, demand in Jan 2015 accounted for 9.14% of total demand in 2015; hydro potential in the same month represented 11.31% of total potential in that year. A clear seasonal pattern arises, particularly in hydro potential, which is at its highest in winter and lowest in summer; instead, demand peaks in January and July. Overall the two (whole) series seem pretty much uncorrelated (the coefficient is -0.14); different seasonal patterns can explain this to some extent. There are wide gaps and trend mismatches in summer, but the two series comove a number of months.

FIGURE A1: Hydropower potential and power demand in mainland Spain 2015-2017.

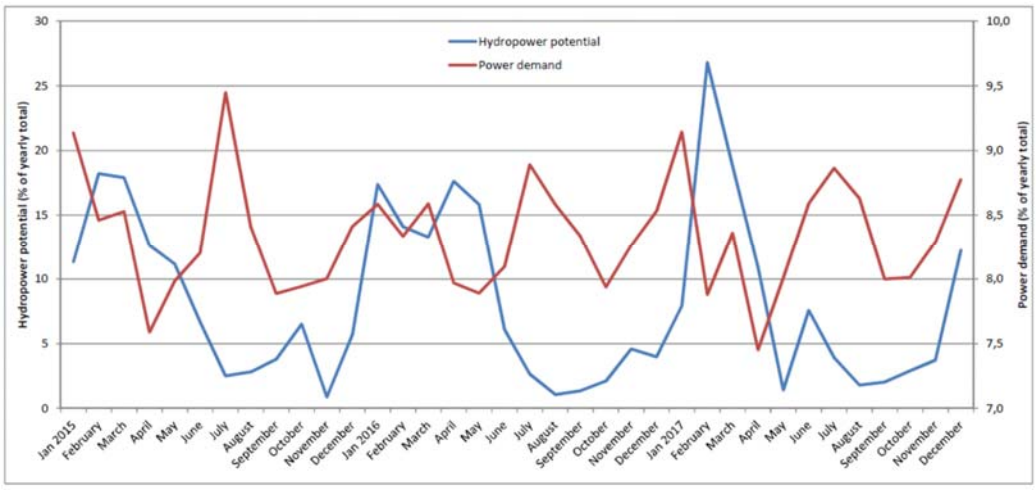

Figure A2 below displays the actual operation profile of pure pumped storage (PHES) plants in Spain. We have collected their hourly generation over the period 2014-2018, i.e. 43,824 observations. Each bar shows the number of hours when their net generation level falls between the bounds shown on the horizontal axis. Even though their aggregate installed capacity amounts to 3,337 MW, their usual net output is quite far from operation at full capacity.

FIGURE A2: Hours with positive net generation from PHES stations, 2014-2018. Source: Own elaboration on REE data.