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Figures of Merit for Wind and Solar PV Integration in Electricity Grids

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In future electrical grids, high levels of Variable Renewable Energy (VRE) penetration including solar photovoltaics (PV) and wind energy is expected. This poses a challenge in system operation and planning especially in balancing electricity demand and supply. This paper examines figures of merit for wind and solar integration in electricity grids. Quantitative tools such as load duration curves, correlation analyses, and the Fourier transform were used to study the intermittency/variability of wind and solar PV power. Time series data on power production from the European Network of Transmission System Operators for Electricity (ENTSO-E), and Réseau de Transport d'Électricité (RTE) were used for the analyses. The analyses illustrate that despite the valuable amount of energy that can be obtained from wind and solar PV, these energy sources cannot be used as baseload power supply. Solar PV power is available for approximately 50% of the time year-round. Wind power output on the other hand can reach very small magnitudes of just a few megawatts several times in a year. More to that, wind is positively correlated over long distances, even exceeding 3000 km and aggregating wind fleets over a large geographic area might not guarantee continuous availability of wind power. Nonetheless, these sources can still be integrated in electricity grids in high proportions, provided intermittency mitigation options such as energy storage, curtailment, and demand-response are implemented.

Keywords: Autocorrelation, Load duration curve, Solar photovoltaics, Spatial correlation, Variable renewable energy

Introduction

The integration of Variable Renewable Energy (VRE) such as wind power and solar photovoltaics (PV) in electricity grids poses a unique set of benefits and challenges. It can reduce transmission and distribution line losses, increase grid resilience, lower generation costs, and reduce requirements to invest in new utility generation capacity. Distributed PV and wind systems can also mitigate reliability issues experienced in developing areas by providing standby capacity capable of offering stable power during times of poor power quality.[1] As automation of transport (e.g., fully electric cars) as well as heat (e.g., thermal pumps) gains popularity, global energy consumption is expected to grow even faster.[2] Recurrent energy shortage and reliance on fossil fuels are key geopolitical challenges that will influence the future of the energy sector.[3] Implementation of Renewable Energy Sources (RES) on a Large Scale is among the most viable solutions to those problems.[4] Because of their possibilities and abundance practically everywhere on the earth, wind and solar photovoltaic (PV) are by far the most exciting renewable energy sources.[5] On the other hand, RES does have its own series of challenges.[6] The foregoing are the most pressing energy issues: (1) transmission loss (intermittency), (2) availability, which varies across time and space, and (3) non programmability, because their output is climate dependent and cannot be planned, though it can be projected.[7] They face cost threat from conventional sources of energy generation, such as fossil fuel-fired power stations, from an economic standpoint.[8] Electrical Energy Storage (EES) with VRE integration has been presented as a potential solution to RES energy challenges, decreasing the effect of transitioning from conventional power generation sources and paving the way for a considerable increase in RES integration into overall production percentage.

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However, being an intermittent energy source, VRE cannot always provide electricity when required, making it highly volatile. It therefore creates a challenge in balancing electricity demand and supply. To integrate these sources in grids, measures need to be taken to ensure that demand is always equal to supply to maintain grid stability. If demand is more than supply, there will be a drop in frequency and if supply is more than demand, there will be an increase in frequency. This is dangerous to the electrical network because the system components are designed to work at a frequency of 50 Hz (or 60 HZ in the case of the USA), with a tolerance level of ±0.5 Hz and any frequency deviations out of these limits can damage the network equipment, leading to grid failure.

This paper therefore examines figures of merit for wind and solar integration in electricity grids. First, several quantitative tools such as Load Duration Curves, Autocorrelation Function, Probability Density Function, and Fast Fourier Transform have been used to quantify the intermittency of VRE. Then, intermittency mitigation options such as energy storage, demand-response, and curtailment have been discussed.

Methodology

The analyses were carried out using the open data published by the European Network of Transmission System Operators for Electricity (ENTSO-E), and Réseau de Transport d'Électricité (RTE), which is the French TSO. The data platforms provide data points on power generation and consumption in Coordinated Universal Time, UTC. RTE provides data restricted to France, whereas ENSTO-E provides data for all member states of the European Union. The analyses were carried out using time series data from the year 2014 to 2018.

To avoid any misleading outcomes in the analyses of the time series data, the below-mentioned actions were carried out:

- All the data sets were proofread before including them in the analysis.
- No alterations were carried out on the data points except on the solar PV data from RTE which had some data points with negative values (−2 or −1) between the period UTC 00:00 to UTC 06:00. Solar PV power output is supposed to be zero during this period because there is no sunlight. Consequently, the values were replaced by zeros.

The countries whose data on wind and solar PV were accessible on the ENTSO-E transparency platform and have been used in the analyses include France, Belgium, Spain, Denmark, Norway, Poland, Estonia, Finland, Latvia, Lithuania, and Romania. Also, in order to carry out spatial correlation analysis, the distance between the wind fleets of each pair of countries was approximated to the shortest air travel distance between the pair of countries using Google maps. These data have been used to construct several figures of merit on wind and solar PV integration in electricity grids.

Results and Discussion

Load Duration Curves (LDC) of Wind and Solar PV

A Load Duration Curve (LDC), also known as a demand frequency distribution curve is a graph that expresses the relationship between time and demand by showing the percentage of time demand is greater or equal to a certain level.[9] A flat load duration curve will mean a more consistent and hence easier to accommodate load throughout the year. However, it does not directly account for the variations that occur in the time series because the data points are sorted in the order of decreasing magnitudes. An LDC, therefore, seeks to answer the inquiry as to whether increasing the capacity of installed VRE can increase the aggregate minimum power output. This is because the annual minimum power output of VRE reflects the permanently available aggregate power output (secured capacity) by which conventional power plant capacity can be reduced permanently.[10]

Solar energy, being intermittent in nature follows a diurnal cycle. That is, it is available for approximately 50% of the time year-round. The LDC of solar PV in France for the years 2014 to 2018 is shown in Fig. 1. Over the years, the percentage of time for which solar PV is available stays the same because the cycle does not change every year. However, the power generated is increasing each year (around 10% per year). Between 2014 and 2018, the total installed solar capacity in France had risen from 5660 MW to 9466 MW. This increase in installed capacity led to an increase in the power that can be produced via solar PV. Therefore, while the generating capacity increases, the power production from solar PV increases as well.

Normalizing the power output of solar PV to its average annual value gives Fig. 2. From this figure, for about 34% of the time, solar PV power output is

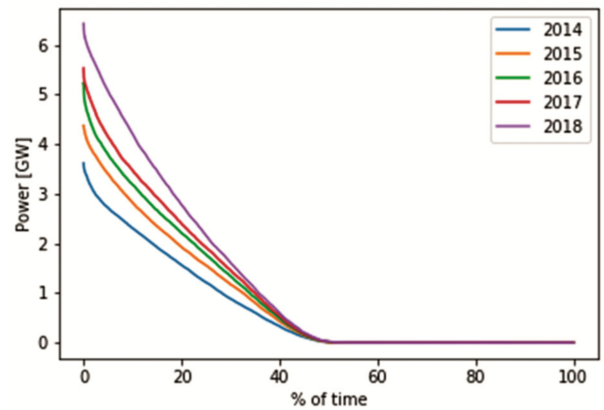

Fig. 1 — Load duration curve for solar PV in France

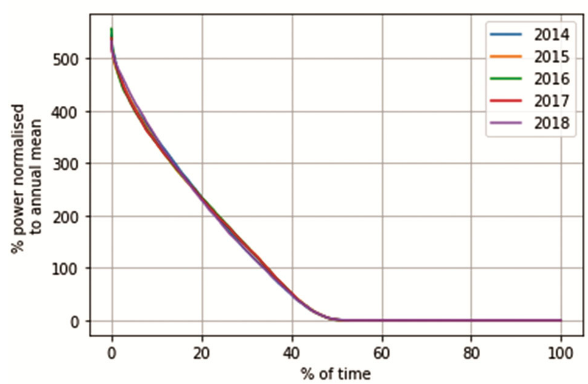

Fig. 2 — LDC of solar PV in France normalised to annual mean value

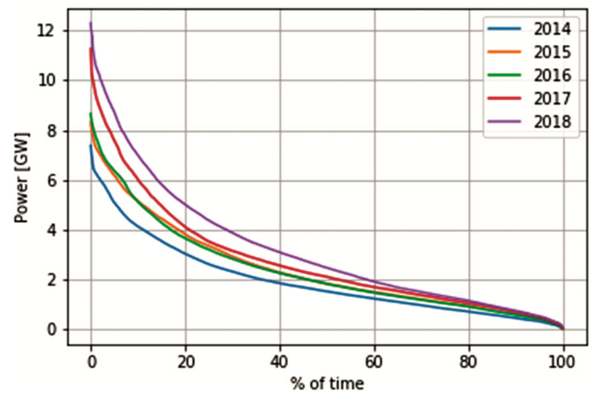

Fig. 3 — LDC of wind power in France

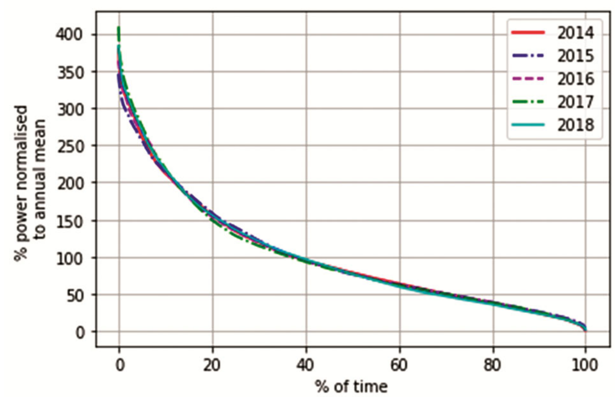

Fig. 4 — LDC of wind power in France normalised to annual mean value

greater than its mean value, even reaching magnitudes of over 500%. Therefore, in periods of its availability, solar PV is a valuable source of energy to be exploited.

For the same installed capacity, wind farms can produce more power than solar PV because wind can be available all round the clock, while solar PV power is only available when there is sunlight. Therefore, the capacity factor of wind is often higher than that of solar PV. Capacity factor refers to the ratio of the average power generated to the rated power over a given period of time. For example, in 2017, the capacity factor of solar PV in France was 14.9%, while that of wind was 21.6%.(11) The LDC of wind power in France from 2014 to 2018 is shown in Fig. 3. Within this period, the installed wind power capacity had risen from 9,285 MW to 15,108 MW. It can be observed in the LDC that an increase in the installed capacity of wind power increases the power that can be produced from it. However, the minimum wind power output in France does not change much. The minimum output power was 26 MW in 2014, 21 MW in 2015, 53 MW in 2016, 62 MW in 2017, and 83 MW in 2018. Therefore, increasing the installed wind power capacity cannot reduce the conventional dispatchable power plant capacity to a perceptible level.

Some interesting observations can also be seen by normalizing the LDC of wind power output to its annual average value as shown in Fig. 4. About 38% of the time, wind power output was greater than its mean annual value from 2014 to 2018, reaching magnitudes of even 420% in 2017. However, the magnitude by which the normalized power output was greater than its annual mean value is not proportional to the installed capacity. Despite the increase in installed wind power capacity from 2014 to 2018, the maximum value by which wind power output was more than its annual mean fluctuated from 380% in 2014, 350% in 2015, 320% in 2016, 420% in 2017, and 380% in 2018. Also, the percentage of time wind power output was more than its mean annual value remained constant at 38% for all the years. Therefore, increasing the installed capacity of wind power will not increase the percentage of time the power output is more than its mean annual value and consequently no guarantee that there will be continuous availability of wind power that could serve as baseload and replace the conventional dispatchable power plant capacity permanently.

Cumulative Distribution Function (CDF) of Wind Power

The frequency distribution of the power output of VRE can be studied by mapping the cumulative distribution of the time series data to the power output, normalised to its nominal capacity.[12] The Cumulative Distribution Function (CDF) is generally used to specify the distribution of multivariate random variables. In this analysis, it helps us to study the variation of wind power output in relation to its installed capacity.

The cumulative distribution versus the power output normalized to the nominal capacity at year-end of the French wind fleet is shown in Fig. 5. It is worth noting that the highest Capacity Factor (CF) was reached in the year 2015 (23%) while the lowest CF was recorded in 2016 (19.7%) even though the installed capacity of wind fleet in 2016 was higher. The CF corresponds to the ratio of the mean power output to the nominal capacity. For a CDF value of 80%, France's wind fleet produced up to 35% of the nominal capacity in 2015, while in 2017, only 30% of the nominal capacity was achieved. That is, the probability that the French wind fleet produced power less than or equal to 35%, and 30% of its nominal capacity in 2015 and 2017 respectively was 80%. It is therefore evident that CF does not correspond to the increasing installed rated capacity, but varies mainly due to the wind conditions throughout the year.

It is also worth noting that the power output from wind does not follow the Gaussian or normal distribution function as shown in Fig. 6. Low power outputs occur more frequently than high power outputs. μ and σ represent the mean and standard deviation respectively.

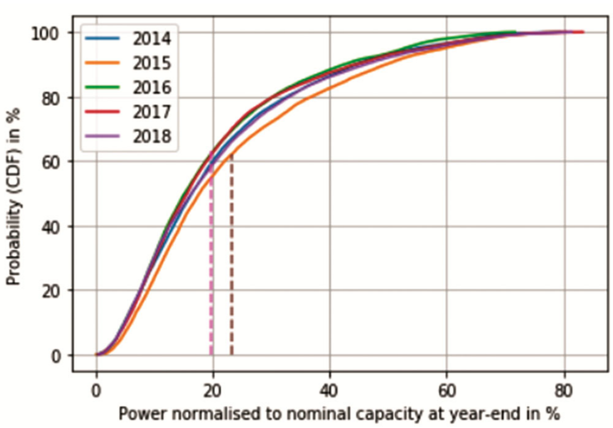

Fig. 5 — Cumulative distribution of wind power normalized to nominal capacity at year-end in France

Autocorrelation Function of Wind and Solar PV Power

Autocorrelation functions have been previously used in renewable energy-related research to determine the importance of daily and yearly cycles in wind speed and temperature profiles. Autocorrelation helps to observe how fast the data changes and shows how well-correlated a signal is with itself under different lag times.[13] The analysis of autocorrelation is a mathematical tool for finding repeating patterns. This is very important for the optimization of demand management, storage optimization, and data acquisition of such systems.[14] The output power of wind turbines is stochastic due to intermittent wind gusts and turbulences. This causes additional interactions with the electrical grid and affects the voltage quality. The power of photovoltaic systems is variable due to alternating clouds. The jumpy characteristic of renewable sources decreases when increasing the spatial size over which the renewable energies are harvested.[15] Pearson's product-moment based autocorrelation function *r(l)* dependent on time lag (*l*) can be calculated with the following equation:

$$r(l) = \frac{\sum_{i=1}^{N-1}(x_i-\bar{x})(x_{i+1}-\bar{x})}{\sum_{i=1}^{N}(x_i-\bar{x})^2} \quad \dots (1)$$

where, l is the lag, which is the time distance between pairs of values in the analysed time series, x_i are the values and $\bar{x}$ is the mean of the time series.

The autocorrelation function of solar PV in France for the year 2018 plotted using Pearson's autocorrelation function is shown in Fig. 7. From the

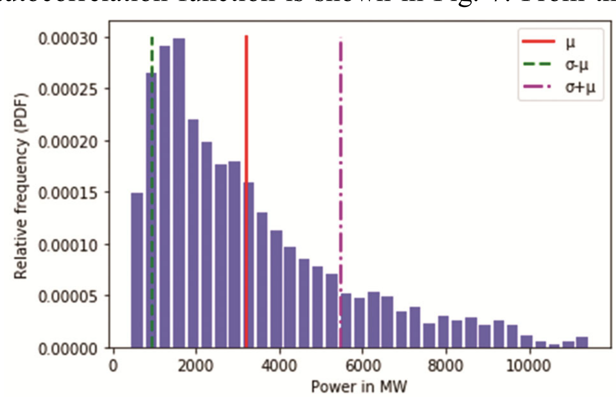

Fig. 6 — Frequency distribution of wind power output of the French wind fleet in 2018

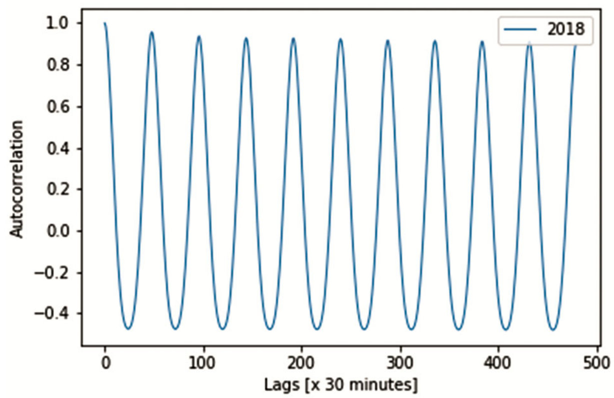

Fig. 7 — Autocorrelation function of solar PV in France

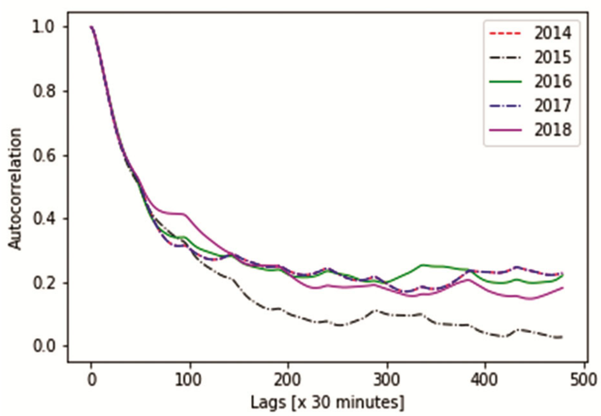

Fig. 8 — Autocorrelation of wind power output in France

graph, the autocorrelation of solar PV varies sinusoidally. The PV output, follows the diurnal cycle as expected. The autocorrelation function keeps a memory of the past. i.e. by knowing the value of the autocorrelation function at any given time, it is possible to predict the value at some future time with a high degree of accuracy.

The autocorrelation functions of wind power in France are shown in Fig. 8. The autocorrelation of wind power is high (≥ 0.7) for the first 720 minutes (24×30), i.e. half a day. The function follows an exponentially decaying pattern as the coefficient falls from 1 to 0 but starts oscillating in an irregular pattern around the zero-coefficient point with an increase in time. The autocorrelation analysis for different years produces similar results, with wind power having a weak autocorrelation coefficient as time increases. Such an exponentially decaying autocorrelation does not have a memory of the past. It will therefore be very difficult to forecast the magnitude of wind power output some days ahead, by knowing the present value of the autocorrelation coefficient.

Spatial Correlation of Wind Power

Correlation mathematically explores the relationship between the observed values of a pair of variables. In this analysis, we seek to evaluate whether and to what extent the cumulative time series for the hourly power output of a pair of national wind fleets **correlate spatially** (depend on the mean distance between them).

The parameters may just have a positive relationship, which means that when one variable's value rises, so does the value of the other. Additionally, the relationship can be negative, implying that when one variable's value rises, the values of the others fall. Lastly, the relationship could be neutral, implying that the factors are unrelated. Correlation is a statistic that ranges from −1 to 1 for totally negatively correlated and perfectly positively correlated data, respectively. The "correlation coefficient" is the term used to describe the calculated correlation. Standard methods like Pearson's correlation can be used to calculate the relationship between two variables with Gaussian distributions. This approach, however, will not work with data which do not possess a Gaussian distribution. Rank correlation approaches must be utilized instead. Methods that measure the relationship between variables that use the ordinal association between the variables than about the exact values are referred to as rank correlation. Ordinal data consists of data with labelled values and an ordering or ranking relationship, such as 'low, medium, and high.[16] Rank correlation can be calculated for real-valued variables. This is done by first converting the values for each variable into rank data. This is where the values are ordered and assigned an integer rank value. The link seen between pair ranked values can then be quantified using rank correlation coefficients. Rank correlation approaches are referred to as nonparametric correlation since no distribution for such variables is inferred.[17]

The spatial correlation analysis carried out here is based on time series data of hourly electricity power generation from wind power in 11 EU countries and the mean distance between the countries for 2018. The total number, n, of possible pairs of country combinations can be calculated from the number, x, of countries as follows:

$$n = \binom{x}{2} = \frac{x!}{(x-2)!2!} \qquad \dots (2)$$

In the case of 11 countries, we have 55 possible country pairs and 55 mean distances between the national wind fleets, which has been approximated in this case as the mean aerial distance between the countries.

In this analysis, Spearman's rank correlation procedure which is resistant to outliers was used because wind power does not follow the Gaussian distribution. Using Google Maps, the mean aerial distance between each pair of countries was determined. The plot of the spearman rank correlation coefficient r_S versus the mean aerial distance between each pair of countries is depicted in Fig. 9. Latvia and Lithuania with a mean aerial distance of 196 km between them, have the highest spearman rank correlation coefficient of 0.743. All the countries with a mean distance of less than 500 km between them have a correlation coefficient greater than 0.5. The correlation coefficients can be approximated by a trendline which decreases exponentially with increase in distance. The trendline has an R-squared value of 0.706. R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, which ranges from 0 to 1, with 1 being the best value.

Apart from the Estonia – Romania pair which have a correlation coefficient of −0.007, with a mean distance of 1,408 km between them, all the pair of countries are positively correlated. The power outputs of the national wind fleets of individual neighbouring countries develop in a largely synchronised manner, and so smoothing effects can barely be identifiable or are limited if the wind fleets are aggregated as illustrated for example in Fig. 10 and Fig. 11.

Fourier Transform

Even though correlation analyses provide information on the variability and predictability of VRE, they do not give sufficient information on frequency and periodicity. The frequency spectrum obtained using Fourier Transforms can provide valuable information on the periodicity of VRE. Fourier Transforms are a series of equations that transform the signal from its original domain (time and space) to a representation in the frequency domain. This is done by computing a sequence of discrete Fourier transforms (DFTs) through various algorithms such as the fast Fourier transform. The equation for the 1D Discrete Fourier Transform is depicted below:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \quad \text{... (3)}$$

The continuous-time signal *x(n)* is sampled every n second to obtain the discrete-time signal X(k), where k is the current frequency (0 Hz to N-1 Hz). Discrete Fourier transforms (DFT) are computed over a sample

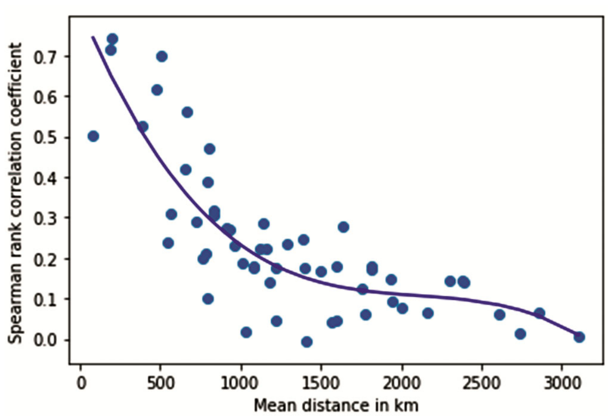

Fig. 9 — Spearman rank correlation coefficient r_s as a function of the mean distance between national wind fleets for 11EU countries, calculated on the basis of hourly power time series in 2018

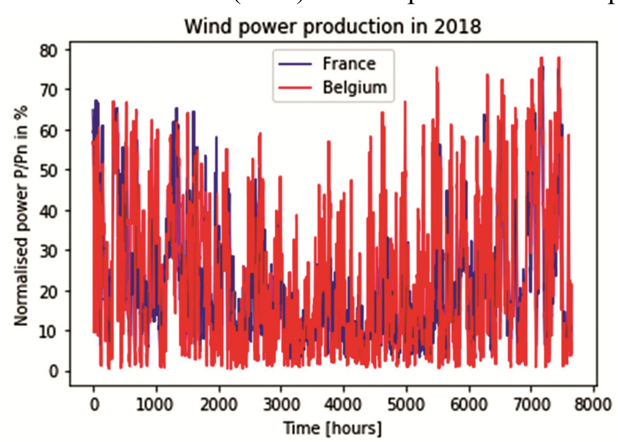

Fig. 10 — Normalised hourly power output time series of a pair of wind fleets in the EU with positive Spearman rank correlation (r_s=0.700) in 2018

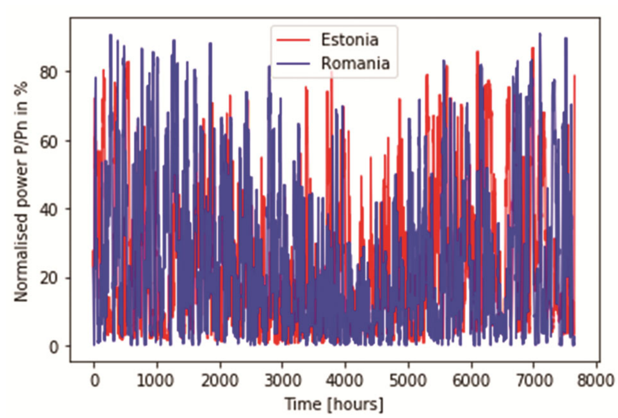

Fig. 11 — Normalised hourly power output time series of a pair of wind fleets in the EU with negative Spearman rank correlation (r_s=−0.007) in 2018

window of N samples, which can span between the entire signal or a portion of it. By finding the Fourier Transform of time series data and plotting the power spectrum, the periodicities and amplitudes of the frequency components can be found.

The FFT spectrum of solar PV power in France for the year 2018 is shown in Fig. 12. The dominant signal has a frequency of 0/day and an amplitude of 2.4 A.U. This dominant signal does not give any information about the periodicity of solar PV power because it is not periodic. However, being the dominant signal, it means that a large part of solar PV power is aperiodic and unpredictable. Nonetheless, the greater proportion of the frequency spectrum is periodic. The second dominant signal has a frequency of 1/day with an amplitude of 1.9 A.U. This corresponds to a period of 1 day (24 hours). Also, the third dominant signal has an amplitude of 0.8 A.U, and a frequency of 2/day, which translates to a period of 12 hours. Therefore, solar PV power variation in each day is similar to that in another, at least qualitatively.

The FFT spectrum of wind power in France in 2018 is shown in Fig. 13. The dominant signal has a frequency of 0/day and an amplitude of 6.8 A.U. This dominant signal does not give any information about the periodicity of wind power because it is not periodic. Also, most of the power spectrum is concentrated at this frequency. This implies that despite the intermittent nature of wind power, it is persistent and always available, at least on a qualitative basis. The remainder of the spectrum is made up of indistinguishable and continuous frequency components with peaks that are less than 0.7 A.U. This is due to the continuous variability of wind power.

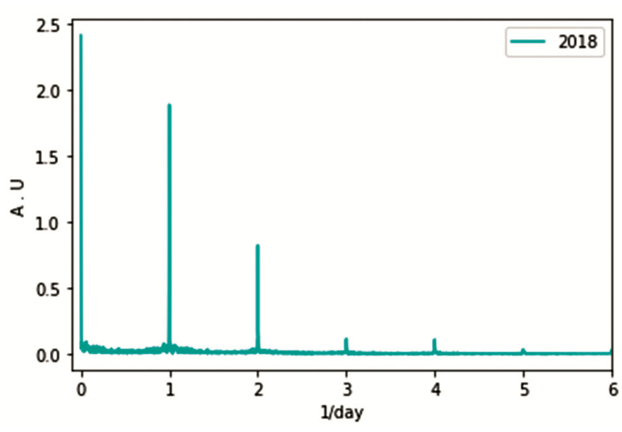

Fig. 12 — Fast Fourier Transform (FFT) of solar PV in France

Wind and Solar Integration and Impact of Flexibility Options

So far, the variability/intermittency of VRE has been discussed. It is evident that VRE is not dispatchable and requires probabilistic techniques to forecast the power output, which can lead to significant errors. From a technical perspective, two things need to be ensured: a balance between instantaneous load and generation (generation side), as well as transmission and distribution (network side).

Several flexibility mechanisms to deal with the variability/intermittency of VRE exist. These include: the use of demand-side, storage, grid extensions, curtailment, and dispatchable generationresponse.[18] When VRE is available in surplus, the surplus electricity can be stored in stationary batteries or electric vehicles. Other forms of storage include pumped hydro plants, where the excess power is used to pump and store water in a damp uphill, which can then be used to produce electricity when needed. Also, the surplus power can be used in the electrolysis of water to produce hydrogen (green hydrogen) or synthetic methane, which are increasingly being considered as alternative fuels to substitute fossil fuels. Curtailment could be thought of as the polar opposite of flexible dispatchable generation. Curtailment is essential once instantaneous VRE generation surpasses original demand in order to maintain supply-demand balance. The impacts of probable net-demand peak reduction and curtailment on the VRE system are examined in this section. Hourly time series data of power demand in France as well as solar PV and wind power output in 2018 were used for the analysis. During this year, solar PV provided 2.1% and wind, 5.76% of the total electricity requirements. This implies that the energy mix between solar PV and wind was 26.7% solar PV and 73.35% wind. The term

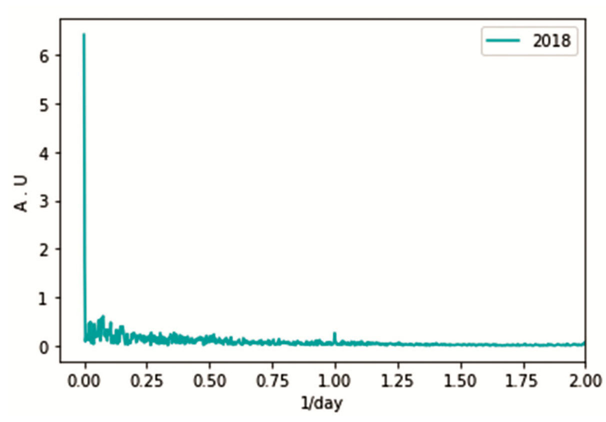

Fig. 13 — FFT of wind power in France

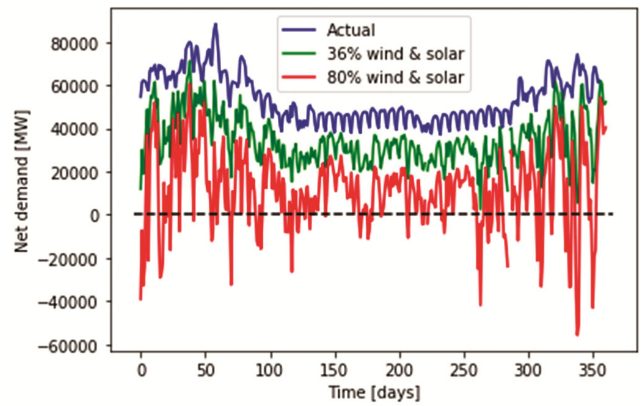

Fig. 14 — Average net daily demand for wind and solar integration in France in 2018

residual demand refers to the original demand less the possibility of VRE generation. The interaction between the demand pattern and power supply for systems with high shares of VRE is a crucial issue which needs to be considered.

The Fig. 14 shows the actual daily average demand (in blue) as well as the residual demand. If wind power is boosted to a proportion of 36% (in green) or 80% (in red), provided that all wind energy can all be collected into the system. As illustrated in the figure, 36% of wind and solar PV integration does not require curtailment, and the curve hits 0 net-demand line once. Increasing the percentage of wind and solar PV integration above 36% will lead to negative net demand values. For example, 80% of wind and solar PV penetration in the system achieved negative values of net demand several times throughout the year. This implies that a surplus of VRE is available and curtailment, storage, or upward demand-response is needed. Also, there are moments when the residual demand almost reached the original demand — which translates to a very small wind power output. These events point to use of standby generation, a downward demand-response strategy or storage.

Apart from variability/intermittency, there are several other challenges for the integration of VRE in electricity grids. Despite their ability to reduce transmission line losses and increase grid resilience by decongesting the transmission grid, they can also create transmission congestion. Wind farms are often far away from industrial or residential areas and consequently, the power produced from wind needs to be transported over long distances to consumption sites. Finding an optimal size for such a transmission network can be complicated. Periods of peak power production do not occur most of the time, and thus, investing in transmission infrastructure to accommodate these periods might not be economical because a large fraction of the transmission capacity will not be used most of the time. On the other hand, under-sizing the transmission line will lead to transmission congestion during periods of peak power production and consequently, power curtailment might be the only option.

Another challenge with integrating VRE into the electric grid is the absence of inertia. Wind and solar do not contribute to the inertia of the grid. Inertia is very important to maintain grid stability. All the generators in the power system rotate at the same frequency, thereby acting as a barrier against abrupt changes in frequency. When power demand spikes, the frequency begins to reduce, and vice versa when power demand decreases. The grid's large spinning mass works as a shock absorber, slowing the rate of change. There is no rotating mass in solar PV. Even enormous wind turbines are fed to the network via a frequency converter, which prevents the rotating mass's kinetic energy from acting as inertia throughout moments with frequency change.[19] As a result, as inertia declines, unexpected variations in frequency induced by changes in electrical production or consumption become faster and greater, making maintaining grid frequency within its own operational limits more challenging.[20–28]

Conclusions

From the load duration curves, solar PV power is available for about 50% of the time in a year which can be accounted for by the diurnal cycle. Wind power on the other hand can be available throughout the year, though with very small magnitudes during some periods depending on weather/seasonal patterns. The autocorrelation function of solar PV power output keeps the memory of the past. Hence, solar PV power output can be predicted with a high degree of accuracy.

The intermittency/variability of wind and solar can be mitigated by the use of demand-side response, storage, grid extension, curtailment, and dispatchable generation. High shares of wind and solar PV power can be integrated in existing grids without the need for curtailment.

Neither the load duration curve, autocorrelation function, nor Fourier transform could give comprehensive information on the intermittency of wind and solar PV. Therefore, a more comprehensive tool is required to model the behaviour of these variable renewable energy sources.

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