Controlling Volatility of Wind-Solar Power In Germany

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Research Article

Keywords: wind-solar, electric, volatility, turbines

Posted Date: December 8th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1142831/v1

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Controlling volatility of wind-solar power in Germany

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Abstract
The main advantage of wind-solar power is the electric power production free of CO$_2$. Its main disadvantage is the huge volatility of the system [national electric energy consumption powered by wind-solar power]. In fact, if this power production, averaged over one year, corresponds to the averaged electric consumption and is intended to replace all other electric power generating devices, then controlling the volatility of this system by using storage alone requires huge capacities of about 30TWh, capacities not available in Germany. However, based on German power data over the last six years (2015 till 2020) we show that the required storage capacity is decisively reduced, provided i) a surplus of wind-solar power is supplied, ii) smart meters are installed, iii) a different kind of wind turbines and solar panels is partially used, iv) a novel function describing this volatile system, is introduced. The new function, in turn, depends on three characteristic numbers, which means, that the volatility of this system is characterized by those numbers. When applying our schemes the results suggest that all the present electric energy in Germany can be obtained from controlled wind-solar power. And our results indicate that controlled wind-solar power can produce the energy for transportation, warm water, space heating and in part for process heating, requiring an increase of the electric energy production by a factor of 5. Then, however, a huge number of wind turbines and solar panels is required changing the appearance of German landscapes fundamentally.
1 Introduction

Apart from nuclear power and hydropower (power from biomass and waste could be mentioned, too), the conventional electric power production by gas and fossil fuel power stations generates \( CO_2 \) as a byproduct. Nuclear power plants do not have this problem, but they have other disadvantages, in particular production of radioactive waste. All these problems do not occur, when electric power is produced by solar panels and wind turbines\([1]\) alone.

Nevertheless, wind-solar power has serious disadvantages too\([2]\), apart from changing the scenery of the landscape the most serious one being the volatile energy production: Weather conditions change rapidly and also on a seasonal scale. As a consequence energy production of wind-solar power fluctuates considerably. How serious the consequences are, depends on two factors: i) the strength of the volatility, ii) the volatility a consumer can tolerate - cf. the key phrase “new thinking”\([3]\).

The problem of volatility is always a consequence of the mismatch between electric power production and electric power consumption (the load). In a first ansatz we will try to remove this mismatch by passive storage devices alone, like pumped-storage plants, for example\([4]\). To obtain the strength of volatility within this scheme, we proceed in the following way: We denote the volatile wind-solar energy production as \( P_v \), the load as \( P_d \) and their integrals as

\[
E_v(t) = \int_0^t P_v(t')dt',
\]

and

\[
E_d(t) = \int_0^t P_d(t')dt'.
\]

We divide \( P_v \) and \( P_d \) into two parts: the average parts \( P_{va} \) and \( P_{da} \), being constant over the year, and the fluctuating parts \( P_{vf} \) and \( P_{df} \), whose average
over the year must be zero. With this we get the condition

\[ P_{va} = P_{da} \]  \hspace{1cm} (1)

To smoothen the power flow of \( P_v \) we apply a storage flow \( P_{sv} = -P_{vf} \) and with

\[ E_{sv}(t) = \int_{t}^{t'} P_{sv}(t') dt' \]

the storage capacity needed is then

\[ E_{svmax} = \max_{t} \{E_{sv}(t)\} - \min_{t} \{E_{sv}(t)\} \]

Replacing \( v \) by \( d \) we get the condition for a smoothened load

\[ E_{sdmax} = \max_{t} \{E_{sd}(t)\} - \min_{t} \{E_{sd}(t)\} \]

Putting consumption and volatile generation together, we get

\[ P_s = P_{vf} - P_{df} \]  \hspace{1cm} (2)

and

\[ E_s(t) = \int_{t}^{t'} P_s(t') dt' \]

\[ E_{smax} = \max_{t} \{E_s(t)\} - \min_{t} \{E_s(t)\} \]

Moreover, taking into account Eq.1, and Eq.2 we obtain after integration

\[ E_d(t) = E_v(t) - E_s(t) \]  \hspace{1cm} (3)
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$E_s$ removes the mismatch between volatile consumption ($E_d$) and volatile energy ($E_v$), generated by wind-solar power.

In order to obtain the functions in the above equations, data of $P_v$ and $P_d$ are required. These are obtained from ref[5]. The data include those of the total electric load and the volatile electric power, consisting of: solar power as well as offshore and onshore windpower. Results are shown in Table 1, and we see two problems emerging. First, comparing the averaged total electric load of Germany, listed in column 2, with the corresponding electric volatile power, listed in column 3, it becomes obvious that Eq.[1] is violated. But since we intend to satisfy the electric energy demand by wind-solar power alone, we need the validity of this equation. Second, whereas the load does not change very much during the six years, the volatile wind-solar power increases by 50% and its various components change considerably. In particular the offshore wind power has increased by a factor of 3 during the six years. To avoid any difficulties connected with these sizeable changes, we treat each year separately and compare the results.

To manage the first problem we assume that the distribution of solar cells and wind turbines is already at its optimum in Germany. In that case we can easily estimate the situation where all average electric energy is delivered by wind-solar power: We just have to multiply the average wind-solar power and its fluctuation part by a scaling factor[2]. Undeniably the distribution of wind-solar power is in reality not at its optimum. Therefore, the scaling is an approximation. However, with increasing volatile power this approximation becomes better and better. And note, the contribution of volatile power has meanwhile passed the 35% mark.

With this in mind we calculate the above functions.
Table 1  Power and storage

| year | load | volatile | diff | solar | offshore | onshore |
|------|------:|---------:|------:|-------:|----------:|--------:|
| 2015 | 57.1  | 12.8    | 39.4 | 4.0   | 0.9      | 90.8   |
| 2016 | 57.2  | 12.7    | 27.6 | 3.9   | 1.4      | 81.0   |
| 2017 | 57.7  | 15.8    | 32.0 | 4.1   | 2.0      | 73.4   |
| 2018 | 57.9  | 17.1    | 23.0 | 4.7   | 2.2      | 78.8   |
| 2019 | 56.4  | 18.9    | 31.5 | 4.8   | 2.8      | 83.9   |
| 2020 | 55.1  | 20.0    | 34.3 | 5.2   | 3.1      | 88.1   |

The numbers in column 2 till 7 (except column 4) present on the left side (averaged over one year) the generated or consumed (cf. column 2) electric power (units are in GW). The values on the right side represent the scaled storage capacities (in TWh units) required, to suppress fluctuations. The scaled storage capacity in column 4 enables appropriate consumption in spite of the volatile wind-solar power and the volatile load.

Denoting the original volatile power, obtained from the measurement data, with $\hat{P}_v$, we get

$$\hat{P}_v \rightarrow P_v = \frac{P_{\text{da}}}{P_{\text{va}}} \cdot \hat{P}_v$$

In the same way we get the scaled quantities $E_v, E_{va}$ and $E_{vf}$. Note that the scaling factor is different for each year. For these scaled quantities the storage capacities smoothing the power flow, have been calculated. The results (in TWh) are in column 3 of Table 1 on the right side.

In a different scenario all power is produced e.g. by solar panels or by offshore or by onshore turbines alone. The scaling is quite analogous to the previous case and the required storage for smoothing the power can be found in columns 5 to 7.

The load has some volatility as well. The storage capacities suppressing fluctuations are depicted in column 2.

A different situation underlies the storage results in column 4. The volatile (scaled) wind-solar power drives the load that shows volatility too. The numbers required when using storage for faultless power transfer are found in this column. Note that this storage is of the same order of magnitude as the storage capacity required to smooth the (scaled) solar-wind power (column 3).
Fig. 1 Fluctuation parts and storage requirements for the year 2017: (Green) dashed line: Fluctuating part $E_{vf}$ of (scaled) volatile energy $E_v$. (Red) dotted line: Fluctuation part $E_{df}$ of integrated load $E_d$. (Black) solid line: (Scaled) fluctuating part $E_{vf}$ of wind-solar energy minus fluctuating part $E_{df}$ of integrated load $E_d$. From the difference between max and min the required storage can be read off. Note that apart from small waves due to the weekends $E_{df}$ varies smoothly and on a seasonal scale only. This is typical for $E_{df}$ in all six years.

A typical example showing the time dependence of the various energies $E_{df}$, $E_{vf}$, and $E_{vf} - E_{df}$ is shown in Fig. 1.

From these results it is tempting to define the strength of volatility power by the storage required to smooth it. But when doing so the conclusion can only be that the volatility of wind-solar power leads to nearly unsurmountable problems, because the storage requirements are huge.

Indeed, volatility has led to the conclusion that energy production, resting essentially on wind-solar power alone, will take us into an economic nirvana[6]. It could be argued that even a total storage capacity of about 85 TWh[4] is in principle feasible by transforming the huge Norwegian hydro dams into pumped-storage plants. However, two facts are obvious: i) The present electric power production has to be multiplied by a factor[2] of about 5, if all transportation, warm water, space heating and a considerable percentage of process heating are switching to electric power as well. With the configurations
presented here so far, this is impossible. ii) Even if we do not consider transportation, warm water, space heating, and process heating, the storage requirements would be so enormous that an export of this wind-solar scheme to many other nations would be out of the question - a bitter disadvantage if Germany wants to be a forerunner.

Fortunately the storage criterion is overestimating the difficulties: This holds true in particular for the big but on a seasonal scale varying part of the energies. So instead of employing storage the varying energies can be better dealt with by a surplus of wind-solar power. In order to proceed successfully we use this alternative. Furthermore we introduce smart meters\cite{7, 8}. Together with a new characterization of volatility, both, the surplus of wind-solar power and the smart meters, are discussed in section 2. We show that through these methods the storage capacity requirements are reduced by a factor of about 30 or more. In section 3 we apply new criteria for optimizing the efficiency of wind turbines, solar cells and their distribution across the country. We show that through these additional features the smart meters need distinctively less flexibility. We think that these results give us the justification for extrapolating to the case, where in addition to the present electric energy production all energy for the total transport, warm water, space heating and a considerable percentage of process heating is exclusively obtained from wind-solar power. This is discussed in section 4. Our conclusions are presented at the end of the paper.

2 Wind-solar power, storage and smart meters

In this section we discuss the situation, in which the electric power generation is taken over by wind-solar power alone.
Normal passive buffers like pumped-storage plants with all their capacity limitations cannot alone control the volatility. Active buffers become necessary to guarantee a safe power delivery. To avoid CO₂ production, we choose wind-solar power itself as active buffers. Assuming as above an already optimal distribution of wind-solar power devices across the nation, the additional wind-solar power can again be expressed by a scaling factor, the strength α, and we get for the wind-solar energy

\[ E_v(t) \rightarrow (1 + \alpha)E_v(t), \quad \alpha = \text{const} \]

The price to be paid for this scheme is a reduced efficiency. This is all the more the case, since at times of low wind-solar power the additional wind-solar power is reduced as well enforcing a larger α value than expected from the average gain in power. To keep α within limits we apply the concept of smart meters. Such devices control the electric consumption very effectively by setting higher consumption prices, when less power is available and lower prices, when there is a surplus of power. Smart meters act like passive buffering devices by moving the peaks of electric consumption to the peaks of wind-solar power.

Of course a detailed simulation of smart meters is intricate. However, we think that the following simulation of smart meters reproduces the basic effects satisfactorily, i.e. shows, how far the smart meter concept is applicable: \( E_d(t) \) has been defined as the energy of electric consumption. Now, if wind-solar production has a surplus, it produces energy corresponding to a demand \( E_d(t') > E_d(t) \) and \( t' > t \). The smart meters now have the task, by decreasing prices for 1kWh to increase consumption and to achieve this \( E_d(t') \). Clearly that is always possible - if necessary, due to exorbitantly low or even negative
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Fig. 2 Delay time $\tau(t)$ [days] for the year 2017. Parameters are: $\tau_B = 3/2$ [days], capacity $\varsigma = 1.0[\text{TWh}]$. Upper figure: $\alpha=1.0$, lower figure: $\alpha = 0.3$. Three numbers, $(n_\lambda, n_\delta, n_\sigma)$, characterize $\tau$: the length $n_\lambda$[days] of the time-interval, in which $\tau$ is moving, the time $n_\delta$[days], during which $\tau < -\tau_B$, and the time $n_\sigma$[days], during which the smart meters are active. These characteristic numbers are given in Table 2. $\tau = 0$ implies: demanded power is delivered without delay, smart meters can pause for the moment.

prices. On the other hand, if wind-solar production is not sufficient, it produces energy corresponding to a demand $E_d(t') < E_d(t)$ and $t' < t$. The smart meters have then the task, by increasing prices for 1kWh to decrease consumption and to achieve this $E_d(t')$. Clearly that is always possible - if necessary, due to exorbitantly high prices. Introducing the delay function $\tau(t)$ we write

$$t' = t + \tau$$

(5)

and the relation $E_d(t) + E_s(t) = E_v(t)$ of Eq.3 is replaced by

$$E_d(t + \tau) + E_s(t) = (1 + \alpha)E_v(t) - E_{dsc}(t).$$

(6)
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Table 2 Characteristic numbers \( (n_\lambda, n_\delta, n_\sigma) \), of the delay function \( \tau \) for 2015 - 2020.

| Year | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|------|------|------|------|------|------|------|
| \( \alpha \) | 3.3  | 9.6  | 5.3  | 10.1 | 3.6  | 3.8  |
| \( \beta \)  | 7    | 9.4  | 5.0  | 9.9  | 3.3  | 3.5  |
| \( \gamma \) | 1    | 9.2  | 4.8  | 9.6  | 3.2  | 3.4  |
| \( \delta \) | 7.3  | 4.7  | 2.8  | 5.9  | 2.6  | 2.9  |
| \( \epsilon \) | 7.7  | 4.5  | 2.6  | 5.6  | 2.4  | 2.8  |
| \( \zeta \)  | 7.1  | 4.3  | 2.5  | 5.3  | 2.3  | 2.7  |
| \( \eta \)  | 1    | 4.0  | 2.3  | 4.9  | 2.2  | 2.5  |
| \( \theta \) | 1.1  | 3.7  | 2.2  | 4.6  | 2.0  | 2.4  |
| \( \iota \) | 1.1  | 3.5  | 2.1  | 4.4  | 1.9  | 2.3  |

Left side of first column: \( \alpha \)-values. Right side: \( \zeta \)-values [TWh]. Obviously small \( \alpha \) values lead to unfavourable results, whereas the influence of \( \zeta \) is less substantial: \( \alpha = 1 \) and \( \zeta = 1 \) [TWh] lead to 9 critical days in 6 years, whereas \( \alpha = 1 \) and \( \zeta = 0.3 \) [TWh] lead to 11 critical days in 6 years. \( n_\sigma \) is the number of days, in which the smart meters are active, in our case \( n_\sigma \approx 10 \) till \( 190 \) out of 365(366) days.

The last term \( E_{dsc} \) is the discarded energy. This new term is necessary, because more energy can be generated than is actually needed. Both, \( E_v(t) \) and \( E_d(t) \) are uniquely obtained from power and consumption data that are updated every 15 minutes. \( E_d \) (and \( E_v \) too) is a strictly increasing function of \( t \). Therefore, given the three values \( t, E_s \) and \( E_{dsc} \), regardless how volatile \( E_v(t), E_{dsc} \) and \( E_d(t) \) may be, there is always a unique solution \( \tau \), allowing the transfer of energy from \( E_v \) to \( E_d \). Nevertheless, here the problem arises.

Positive \( \tau \) means that all power, not up to \( t \) but up to \( t + \tau \), has to be consumed at time \( t \). As mentioned above, smart meters can achieve this by charging low prices. But there is a limit \( \tau_B \) beyond which prices must be unreasonably low or even negative in order to achieve consumption in advance up to \( t + \tau \). Therefore we require:

\[
\tau \leq \tau_B
\]

To avoid \( \tau > \tau_B \) electric power leading to \( \tau > \tau_B \) is discarded as ‘wasted’ power and is removed from the system (see below). Since this ‘wasted’ power
can be (nearly) arbitrarily high $\tau_B$ becomes a perfect barrier for $\tau$. But there is a limit $-\tau_b$ for $\tau$ as well, below which the prices must be unreasonably high to enforce $E_d(t + \tau), \tau < -\tau_b$. Naturally $\tau_b \approx \tau_B$, and for simplicity we set $\tau_b = \tau_B$. Therefore we also demand:

$$\tau \geq -\tau_B$$

In contrast to the barrier $\tau_B$ there is no procedure to always keep $\tau$ above $-\tau_B$ for any value $\tau_B$, since there is no unlimited power that we can put into the system. But we can form an optimized procedure for the delay function $\tau$: Thanks to the installation of smart meters a quasi additional storage is obtained with its maximum given by $E_d(t + \tau_B) - E_d(t - \tau_B)$. We try to keep this additional storage filled implying i) $\tau \to \tau_B$, whenever possible. Due to this constraint and a second one, ii) at anytime trying to keep $E_s$ completely filled under the constraint i), a unique function is obtained for the storage $E_s(t)$. And $E_{dsc}$ becomes now unique too with the constraint iii): whenever there is an overflow of $E_s$, that overflow of power is added to $E_{dsc}$. With these prescriptions we have maximum reserves retained for weak wind-solar weather conditions, and a function $\tau_M(t)$ is obtained with the highest possible absolute minimum $\tau_{Min}$ and the shortest dwelling time $n_\delta$ [days] in the domain $\tau < -\tau_B$. However, quite often $\tau \to \tau_B$ is too strict. Depending on the weather forecast it can be replaced by $\tau \to 0 = \tau_{B0}$ for some time without changing $n_\lambda$ and $n_\delta$. Note that the limit $\tau \to 0$ is important, because in a time interval with $\tau = 0$ no smart meters are needed. In our simulation we mimic the forecast via tests of the alternative $\tau \to 0$ by successively replacing the upper barrier $\tau_B$ with $\tau_{B0} = 0$ for each day and by computing $\tau(t)$ anew. If the new $\tau(t)$ has unchanged $n_\lambda$ and $n_\delta$, we leave the upper barrier at $\tau_{B0}$ for that day,
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otherwise we move it back to $\tau_B$. In this way we get all the days, in which $\tau_B$ is replaced by $\tau_{B0}$. Computing $\tau(t)$ for the last configuration again delivers the days of the year with $\tau = 0$ and therefore all days $n_{\sigma}$ with $\tau \neq 0$. Only in the latter case the smart meters are active. A typical delay function $\tau$ is shown in Fig. 2. Of particular importance is the interval $[\tau_{\text{min}}, \tau_B]$, in which $\tau$ is moving controlled by smart meters. Note, that the length $n_\lambda$ of the interval $[\tau_{\text{min}}, \tau_B]$ is approximately independent of $\tau_B$. (In the ideal case of smooth consumption the approximation would become exact). Therefore we have some freedom of fixing $\tau_B$. Here we set $\tau_B = 3/2 \text{[days]}$ in most cases. Energy consumption more than this time in advance seems to be awkward. And we know the essentials of the delay function, if we have the three characteristic numbers $(n_\lambda, n_\delta, n_\sigma)$ introduced above.

The three characteristic numbers of $\tau$ are listed in Table 2. Looking at this table we recognize: First, the conditions for solar-wind power are good during the years, except for the years 2015 and 2017. Second, small $\alpha$-values lead to unsatisfactory results, whereas the influence of the storage capacity $\varsigma$ is less substantial: $\alpha = 1$ and $\varsigma = 1 \text{[TWh]}$ lead to 9 critical days in 6 years whereas $\alpha = 1$ and $\varsigma = 0.3 \text{[TWh]}$ lead to 11 critical days in 6 years. This weak dependence on $\varsigma$ will become important for our conclusions in chapter 4.

Third, it is possible to generate Germany’s presently required electric power by solar-wind power alone, if the conditions are those of the last 6 years and if the consumers are content with smart meters controlling a domain of $[-3/2, 3/2]$ [days]\(^1\).

While getting the energy functions $E_d$ and $E_v$ by power integration we repeatedly encounter the situation, that $\tau = \tau_B$ or $\tau = \tau_{B0}$ and the storage $E_s$ is full. In this situation an overflow quite often occurs and part of the

\(^1\)To deal with the ‘critical days’ $n_\delta$ should not be a problem, as long as there are only a few of them. For example electric vehicles could be exploited as ‘virtual power plants’[11].
Fig. 3  'Wasted' power. $\alpha = 1$, $\varsigma = 1[TWh]$, $\tau_B = 1.5$ days for the year 2017. This power is generated, if the surplus wind-solar devices work all the time generating maximum possible power. (Black) solid line: 'Wasted' power averaged over $1h$. (Red) dashed line: 'Wasted' power averaged over one year. The averaged value is $57.7$ GW. The 'wasted' power has not only sharp high peaks but longer powerless time intervals as well.

incoming power has to be discarded to prevent increase of $\tau$ beyond $\tau_B$ or $\tau_{B0}$ respectively.

The 'wasted' power arising by overflow of $E_s$ need not be small at all. In fact, if all possible power is generated, the averaged power amounts to

$\approx (1 + \alpha) \cdot 60GW$ (cf. table 1) and thus the average of 'wasted' power to

$\approx \alpha \cdot 60GW$. Getting rid of it directly is one way. This can be accomplished by reducing the wind-solar power generation, as soon as 'wasted' energy begins to build up. The advantage of this procedure would be, that the strain on the electricity network would not be essentially higher than for $\alpha = 0$.

Exploiting this 'wasted' power for processes, e.g. for electrolytic and other chemical processes, would be an alternative. However, one has to keep in mind that the surplus power is really extremely volatile, as can be seen from Fig.3. Apart from high peaks there are - more important - periods, even weeks, when there is no 'wasted' power available.
In our opinion the three characteristic numbers \((n_\lambda, n_\delta, n_\sigma)\) of the delay function \(\tau\) are a realistic indicator for the volatility of the system. Having determined the domain, in which smart meters can be deployed, i.e. after fixing \(\tau_B\), - in our case \(\tau_B = 3/2\) days - the characteristic numbers \((n_\lambda, n_\delta, n_\sigma)\) can be determined from the power and load data as functions of the strength \(\alpha\) and the storage capacity \(\varsigma\), cf. Table 2. If \(n_\lambda \leq 2\tau_B\), everything is fine. If not, then the number \(n_\delta\) of days, where this inequality is violated, becomes important. \(n_\sigma\) is the number of days, in which the smart meters are active, in our case \(\approx 30\) out of \(365(366)\) days are typical values.

The absolute costs per kWh depend on assumptions, about how prices will develop in the future, and which indirect costs need to be included in the calculation and which not. In fact, the estimates fluctuate strongly[2, 12, 13]. However, the relative increase of the running costs per kWh due to the ‘wasted’ power can be assessed: For a small contribution of wind-solar power - so small, that peaks do not overshoot consumption - let the running costs be \(w_{small}[\text{€}/\text{kWh}]\) on average. However, we do not deal with a small contribution. Instead an average demand of \(\approx 60\text{GW}\) must be met. Following the surplus power approach this demand requires an average production of \((1 + \alpha) \cdot 60\text{GW}\). Therefore, the increase of the running costs is \(w_{small} \rightarrow w_{small} \cdot (1 + \alpha)\) and the relative increase is given by \(\alpha\).

3 Importance of weak energy regimes, other options

At first sight it may seem obvious that wind-solar power should have its nominal power at high winds, at high sun radiation and moreover in regions with high winds and high sun-radiation, respectively. But the surplus wind-solar power becomes important, once the wind-solar power production is weak,
and therefore weak-wind turbines and solar cells with good performance in low light conditions will be essential for good surplus power production. Weak-wind turbines having blades enlarged by a factor $\sqrt{\beta}$, greater height and consequently higher wind speed enlarged by a factor $\left(\gamma^{1/3}\right)$, provide an increase of power generation by a factor of $\beta \cdot \gamma$. We choose $\beta \cdot \gamma = 2$. This doubles the surplus power production in the low-wind regime, $P_{\text{low}} = 2 \cdot P$. In the high wind regime, however, the power production saturates, since these turbines have a reduced nominal power $P_{\text{nom}}$. This justifies the ansatz

$$P_{\text{low}}(t) = P_{\text{nom}} \cdot \tanh (\beta \cdot \gamma \cdot P(t)/P_{\text{nom}}), \quad \beta \cdot \gamma = 2$$

Weak-light performance of solar cells depends on the material used. Mono-crystalline PV modules, multi junction with selected band gaps and in the future the new generations of DSSCs may have good weak light performance. And we assume that with good weak light performance the generated power can increase - as in the wind power - by a factor of 2 in the weak-light regime too. (This approximation may be crude but is also less important). So we choose for the total surplus power (here denoted as $P_{\text{low}}$) the ansatz

$$P_{\text{low}}(t) = P_{\text{nom}} \cdot \tanh (2P_{\text{v}}(t)/P_{\text{nom}}), \quad P_{\text{nom}} = P_{\text{va}} \cdot \eta$$

$$E_{\text{vlow}}(t) = \int_0^t P_{\text{low}}(t')dt'$$

$$E_d(t + \tau) + E_s(t) = E_v(t) + \alpha E_{\text{vlow}}(t) - E_{\text{dsc}}(t)$$

To demonstrate the importance of low energy production, we have selected a very low nominal power $P_{\text{nom}}$ for $P_{\text{low}}$:

$$P_{\text{nom}} = P_{\text{va}} \cdot \eta$$

$^{2}$In the scaling factor used here the internal ratio between solar power and wind power is 1:2 till 1:3, cf. Table 1
Fig. 4 \( \tau \) functions, when low-wind and weak-light devices are used. Lower figure: \( P_{\text{nom}} = \frac{2}{3} P_{\text{va}} \). Upper figure: \( P_{\text{nom}} = P_{\text{va}} \). Parameters are: \( \alpha = 1 \), capacity \( \varsigma = 1[\text{TWh}] \), year: 2017.

with \( \eta = 1 \) and \( \eta = 2/3 \). In fact, the average wind \{solar\} power is about four \{ten\} times less than the nominal power of normal wind turbines and normal solar cells.

Typical curves of \( \tau \) are presented in Fig. 4. Our calculations show the following:

- \( \tau_B = 3/2 \) [days], \( \eta = 1 \): \( \tau \) does not leave the domain \([-3/2,3/2]\) in all 6 years.
- \( \tau_B = 3/2 \) [days], \( \eta = 2/3 \): \( \tau \) leaves the domain \([-3/2,3/2]\) only in 2017 for 1.8 days.
- \( \tau_B = 1 \) [days], \( \eta = 1 \): \( \tau \) leaves the domain \([-1,1]\) only in 2015 and 2017 for 5.6 days in total.
- \( \tau_B = 1 \) [days], \( \eta = 2/3 \): \( \tau \) leaves the domain \([-1,1]\) only in 2015 and 2017 for 10.1 days in total.
The distinctly better outcome for the delay times $\tau$ is obvious in spite of the low nominal power $P_{low}$. This emphasizes the importance of good performance in weak wind and low light situations.

We have no firm conclusions about the improvement of the results, when using offshore wind turbines. We have encouraging results for the year 2019 but for the year 2017 we have not got an improvement. As can be seen from Table 1 the contribution of offshore devices to the energy generation was still quite small in 2017. This may explain the controversial results.

Using solar cells as surplus power alone does not seem to be a good idea.

Looking at the characteristic numbers for 2017 with $\alpha = 1$, $\varsigma = 1$[TWh] and $\tau_B = 3/2$ [days] we find $(n_\lambda = 5.3, n_\delta = 22.2, n_\sigma = 72)$. The reason for this disappointing result is the low irradiation during the winter months, not compensated by wind power[23].

4 Adding up all possible electric energy in Germany

In the two preceding sections the possibility of applying wind-solar power without excessive use of storage devices has been demonstrated. However, we only discussed the case of replacing the present electric energy production by wind-solar power. But this amounts to about $20\% \approx 60GW[1, 2]$ averaged over the year, whereas the total energy production amounts to $\approx 300GW$, (averaged over the year). 80% consists of energy production on a fossil or gas basis for transport, warm water, space heating and process heating. Converting this non electric energy production into electric energy production should be possible, not completely, but to a large extent.
Therefore, the question is inescapable: Can all this electric power be generated by wind-solar power alone. Let us look at the consumption part first. The electric power curves of consumption did not differ much in the years 2015-20 and were characterized - apart from small waves due to the weekends - by large but slow changes on the summer-winter scale. We think that this behavior is intrinsic and can be ascribed to the fact that there is no reason for most of the industry and private customers to drastically change their habits within days. Therefore we expect slowly changing consumption curves, when switching to electric power. And such curves represent minor difficulties. In contrast the volatile wind-solar power represents a major problem. But this part can be estimated by simple scaling as in section 2, leading to a scaling factor of 5. This means that the $\tau$ functions, their characteristic numbers and the domains, controlled by smart meters, essentially remain the same. But the number of devices and the storage capacities have to be multiplied by a factor of 5. According to our calculations in chapter 2 a storage capacity $\varsigma$ in the range of $1.5 - 5 TWh$ will now be required.

Furthermore we can argue that in spite of its enormous volatility at least part of the now huge 'wasted' power can be used for chemical, in particular electrolytic processes, by which artificial fuel can be produced, e.g. for airplanes. This would reduce the required wind-solar energy and the scaling factor.

Nevertheless, the huge power requirements represent an enormous challenge. Let us discuss the solar part first.

The scaling factor we have to use, requires a ratio between wind and solar power of $\approx 2 : 1$ or $3 : 1$. Thus the solar devices have to generate an averaged power (yet without smoothing) of nearly 100GW, and the question

$^3$cf. Fig.1

$^4$To convey an idea what a TWh means: If every citizen of Germany would own 10 car batteries with 100 Ah storage capacity each, then the total capacity would correspond to 1TWh.
arises whether this is possible, since the capacity factor of solar cells is dismal for Germany\cite{24, 25}: about 10%. First numeric calculations dealing with this question presented unfavourable answers\cite{26}. With continuously increasing power of computer codes taking into account higher levels of details, in particular structures of roofs\cite{27} and facades\cite{25} this question has now been answered convincingly in the affirmative. Smoothing requires another (averaged) \( \approx 100 \text{ GW} \) in our approach. Even that becomes possible. However, then nearly each roof and possibly part of the facades in Germany have to be covered with solar devices\cite{25}.

The needed number of wind turbines is enormous too. Their capacity factor amounts to\cite{28} 25\%, meaning that an averaged electric wind power of \( \approx 250\text{GW}[1][2] \) corresponds to a nominal power\footnote{The capacity factor of offshore wind turbines is larger and amounts to nearly 40\%. But this would become important only, if offshore wind turbines would account for the largest share.} of 1000 GW. This means 650000 \{170000\} wind turbines of the 1.5\text{MW} \{6\text{MW}\} type (height 120m \{200m\}) are needed to produce this averaged power. But that is not enough, since the power must be controllable. In our approach this also leads to multiplying the number of wind turbines by a factor of \((1+\alpha)\), \(\alpha \approx 1\).

5 Conclusions

Is it possible to switch all of Germany’s present electric energy production to wind-solar power? The answer depends on how the enormous volatility of wind-solar power can be controlled. Our ansatz suggests marginalizing the formidable volatility by i) adding a substantial surplus of wind-solar power ii) installing smart meters\footnote{In our calculations smart meters control a domain of \([-3/2, 3/2][\text{days}]\) (section 2), and domains down to \([-1, 1] [\text{days}]\) (section 3) respectively - with the exception of a few critical \((n_\delta)\) days.}, iii) partly selecting different kinds of wind turbines and solar devices. iv) introducing a novel function describing this volatile system. The new function, in turn, depends on three characteristic
numbers, which means, that the volatility of the system is characterized by those numbers.

When doing all this the results are encouraging: The electric storage capacity needed will be reduced to 0.3TWh - 1TWh.

The prize to be paid will be a \( \approx 100\% \) surplus of wind-solar power devices compared to the situation in which only the averaged wind-solar power production matches the averaged power consumption.

Our precise power data\(^{[5]}\) extend over the 6 years 2015 -2020, a period sufficient to show that wind-solar power is promising. And based on the present data, measured every 15 minutes during the period 2015 - 2020, our approach avoiding excessive passive storage leads to the following conclusions: First, our approach is applicable to electric energy production in Germany as well as in other nations that do not have access to huge storage capacities. Second, our approach leads to the prediction, that Germany’s present electric power demand can be supplied by wind-solar power alone. Third, our approach does no longer exclude the hope that even if most of Germany’s energy production switches to electric energy - which means an increase by a factor of about \( 5^{[2]} \) -, this energy can be delivered by wind-solar power in a controlled fashion when applying our measures described above.

However, no matter how we slice it, the number of required solar cells and wind turbines will become tremendous: Only to satisfy at least the averaged consumption demand, nearly every second roof and possibly a significant part of facades has to be covered with solar cells. Moreover 650000 \{170000\} wind turbines of the \( 1.5MW \{6MW \) type (height\(^{7}\) 120m \{200m\}) become necessary. But this arrangement, tremendous, as it is, succeeds only in setting equal the averaged consumption and the averaged wind-solar energy generation. The wild volatility is fully present and to control it requires a challenging effort.

\(^{7}\)The Cologne Cathedral has a height of 157m.
- the subject of this paper. We offer a successful configuration that does not require much storage capacity. The price to be paid is to approximately double the already large number of wind turbines and solar panels. The running costs will equally rise by \( \approx 100\% \).

The total number of devices will be so enormous\(^8\) that the scenery of the landscapes will change\(^9\). Provided this fact is accepted by the public, wind-solar power - according to the results of this paper - will have a realistic chance of becoming the leading generator of energy - in Germany and in other nations as well.

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\(^8\)Germany’s area is 360’000 km\(^2\).

\(^9\)How far offshore wind-power can ease the situation, in particular decrease the huge number of onshore wind turbines, is a point beyond the scope of the present paper.
All consumption and production data of 2015-2020 were obtained from ENTSO-E, the 'European Network of Transmission System Operators for Electricity', cf. https://transparency.entsoe.eu/generation/r2/actualGenerationPerProductionType/show.

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6 Declarations

- **Funding:** No funding was received for conducting this study.
- **Conflicts of interest:** The author has no relevant financial or non-financial interests to disclose.
- **Ethics approval:** No ethical approval is required for this research.
- **Consent to participate:** This research does not require a consent to participate.
- **Consent for publication:** This research does not require a consent for publication.
- **Availability of data and materials:** The datasets generated during and/or analysed during the current study are available on reasonable request.
- **Code availability:** Code has been developed in Python and is available on reasonable request.
- **Authors’ contributions:** There is only one author.