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Energy supply based on wind-solar power in Germany

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Abstract
Wind-solar power has an intrinsic huge volatility and the obvious question arises, is it possible to marginalize it to an extent that the power generation can sufficiently be synchronized with the electric power consumption being volatile as well. We present a novel function describing the volatile system as a whole. The new function, in turn, depends on three characteristic numbers, which means that the volatility of this system is characterized by those numbers. Using the data of the total electric power consumption and the total wind-solar power generation in Germany for the last seven years (2015–2021) taken every 15 minutes we determine the characteristic numbers from these data and get the result that marginalizing the volatility is possible with a minimum of required storage capacity, provided (i) a surplus of wind-solar power is supplied about doubling the number of devices, (ii) smart meters are installed, (iii) a different kind of wind turbines and solar panels is partially used. Our results suggest that all the present electric energy required in Germany can be obtained from wind-solar power if (i), (ii) and possibly (iii) are fulfilled. And our results indicate that, because of the minimal necessary storage capacity, controlled wind-solar power can in addition produce the energy for transportation, warm water, space heating and in part for process heating, requiring an increase of the electric energy production in total 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. Our method can be applied to the wind-solar power problem of any country provided a reliable basis of power data exists over a sufficiently long period.

Keywords Volatility · Storage · Onshore · Offshore · Weak-wind turbine · Low-light solar cell · Smart meters

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 consists in 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].

An obvious idea for attenuating these fluctuations consists in generating hydrogen [4] and methane [5] by electrolysis and subsequent methanation, whenever there is a surplus of wind-solar power (key phrases are 'green hydrogen' and 'power to gas') and to use the gas for heating or chemical reactions or to generate electric energy e.g. for fuel cells [4] from this gas. This

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certainly indirect way of obtaining at last electric energy from a surplus of that energy poses further problems: The conventional production of hydrogen on fossil basis (keyword 'gray hydrogen') has advantages of low-cost, maturity in technology, and large-scale application. Furthermore, since no breakthrough has occurred yet in the developments of fuel cell power plants [6] the efficiency of hydrogen gas power plants is intrinsically restricted by Carnot's law.

In the present paper we follow a different scheme: We will deal with the problem of attenuating and controlling volatility without taking into account gas power plants or using 'power to gas' schemes. In Sect. 2 our approach consists of using the minimum necessary wind-solar power. The idea is to save energy and material. In this situation all the small and large fluctuations of electric power and consumption must be suppressed by a sufficiently large storage capacity alone. The calculations of this case are straightforward but (i) the schemes and tools derived will be needed in the following sections, (ii) for the first time calculations are compared with real German data over the period of the last 7 years [7]. The results are discouraging, not only for the present but, when extrapolating, even more so for the future: The required storage will be prohibitively large, clearly more than 100 TWh are possible. Therefore, if we take the required storage capacities as a measure for the strength of volatility, the conclusion can only be that the volatility of this system is uncontrollable. In Sect. 3 we develop novel equations that include surplus power. With this power at hand the excessive storage emerging in Sect. 2 can be avoided. In fact, the varying energies, in particular those parts that change on a seasonal scale are much harder to be marginalized by huge storage capacity, than by massive surplus of wind-solar power together with minimum store capacity. Therefore we select this alternative adding the concept of smart meters [8, 9]. We derive three numbers that characterize the volatility in a realistic manner. Applying these novel tools the volatility of the German electric power data is analyzed for the first time over a seven year period: 2015 till 2021 (load-, solar-, offshore- and onshore-data, taken every 15 min). The conclusion is: All the present electric energy required in Germany can be obtained from wind-solar power provided a surplus of wind-solar power is supplied about doubling the number of devices. Furthermore we show that due to the surplus power the storage capacity requirements are reduced by a factor of about 30 or more. In Sect. 4 we apply new criteria for optimizing the efficiency of wind turbines, solar cells and their distribution across the country. We show that by these additional features the smart meters need distinctively less flexibility. We think that all these results together 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 Sect. 5. Our conclusions are presented at the end of the paper.

2 Minimum wind-solar power and storage capacity

In this section we deal with the situation, in which any surplus of wind-solar power is avoided to save energy. In that case we have to remove any mismatch by passive storage devices, like pumped-storage plants, for example [10]. To obtain the strength of volatility within this scheme, we proceed in the following way: We denote the volatile wind-solar power production as P_v, the load as P_d and their integrals as

$$E_v(t) = \int^t P_v(t')dt',$$

and

$$E_d(t) = \int^t P_d(t')dt'.$$

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

$$P_{va} = P_{da}. \tag{1}$$

To smooth the power flow of P_v we apply a storage flow $P_{sv} = P_{vf}$, and with

$$E_{sv}(t) = \int^t P_{sv}(t')dt',$$

the storage capacity needed is then

Table 1 Power and storage

Year	Load	Volatile	Diff	Solar	Offshore	Onshore
2015	57.1#11.4	12.8#39.4	– #37.1	4.0#128.8	0.9#112.1	7.9#90.8
2016	57.2#12.5	12.7#27.6	– #25.1	3.9#138.2	1.4#69.5	7.4#81.0
2017	57.7#13.6	15.8#24.0	– #26.5	4.1#133.5	2.0#58.4	9.7#73.4
2018	57.9#12.8	17.1#23.0	– #15.7	4.7#135.2	2.2#69.6	10.2#78.8
2019	56.4#11.4	18.9#31.5	– #24.5	4.8#131.6	2.8#49.2	11.4#83.9
2020	55.1#16.6	20.0#42.3	– #37.4	5.2#134.8	3.1#70.6	11.7#88.1
2021	57.7#11.4	18.3#25.0	– #25.5	5.3#131.8	2.7#80.8	10.2#68.9

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

$$E_{svmax} = \max_t\{E_{sv}(t)\} - \min_t\{E_{sv}(t)\}.$$

Replacing *v* by *d* we get the condition for a smoothed load

$$E_{sdmax} = \max_t\{E_{sd}(t)\} - \min_t\{E_{sd}(t)\}.$$

Putting consumption and volatile generation together, we get

$$P_s = P_{vf} - P_{df}\,, \tag{2}$$

and

$$\begin{aligned} E_s(t) = &\ \int^t P_s(t')dt' \\ E_{smax} = &\ \max_t\{E_s(t)\} - \min_t\{E_s(t)\}. \end{aligned}$$

Moreover, taking into account Eqs. (1), and (2) we obtain after integration

$$E_d(t) = E_v(t) - E_s(t). \tag{3}$$

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. [7]. The data include those of the total electric load and the volatile electric power, consisting of: solar power as well as offshore and onshore wind power. 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 seven 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 seven years. To avoid any difficulties connected with these sizable 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 30% mark.

With this in mind we calculate the above functions.

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

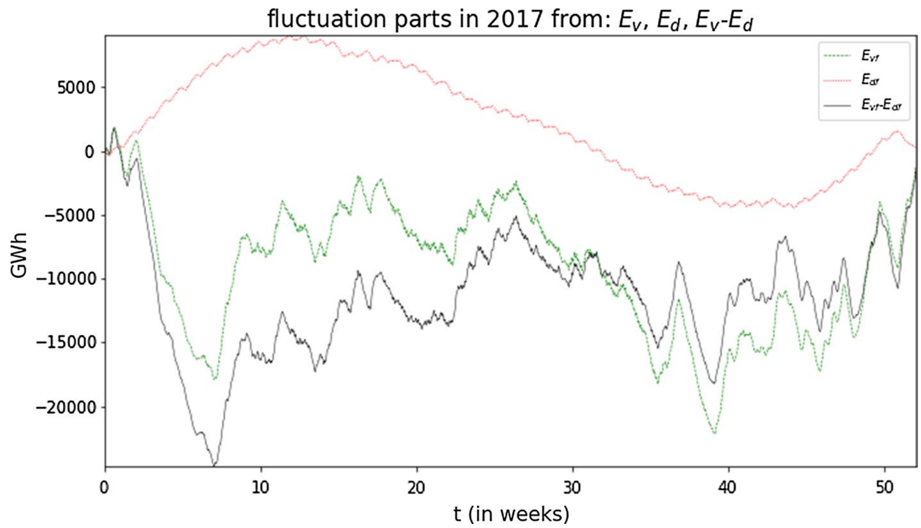

Fig. 1 Fluctuation parts and storage requirements for the year 2017: (Green) dashed line: Fluctuating part E_{vf} of (scaled) volatile energy E_v. (Red) dotted line: Fluctuation part E_{df} of integrated load E_d.(Black) solid line: (Scaled) fluctuating part E_{vf} of wind-solar energy minus fluctuating 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 on a seasonal scale only. This is typical for E_{df} in all seven years

$$\hat{P}_v \rightarrow P_v = \frac{P_{da}}{\hat{P}_{va}} \cdot \hat{P}_v. \tag{4}$$

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 5–7.

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) wind-solar power (column 3).

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 without additional conventional power plants 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 [11]. It could be argued that even a total storage capacity of about 85 TWh [10] 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. But all these problems become soluble, if we allow surplus power and smart meters. This will be shown in the next section.

3 Wind-solar power, storage and smart meters

In this section we discuss the situation, in which - as in Sect. 2 - the electric power generation is taken over by wind-solar power alone. But storage is expensive or even not available, and therefore, in contrast to Sect. 2, we try to minimize the storage capacity. Then active buffers become necessary to guarantee a safe power delivery. And to avoid CO_2 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

$$E_v(t) \longrightarrow (1+\alpha)E_v(t), \quad \alpha = const.$$

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 [8] 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 [12].

Of course a detailed simulation of smart meters is intricate [13]. 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 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 1 kWh 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

$$t' = t + \tau, \tag{5}$$

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

$$E_d(t+\tau) + E_s(t) = (1+\alpha)E_v(t) - E_{dsc}(t). \tag{6}$$

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 min. 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 τ, allowing the transfer of energy from E_v to E_d. Nevertheless, here the problem arises.

Positive τ 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 τ_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:

$$\tau \le \tau_B.$$

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 τ_B becomes a perfect barrier for τ. But there is a limit $-\tau_b$ for τ 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:

$$\tau \ge -\tau_B.$$

In contrast to the barrier τ_B there is no procedure to always keep τ above $-\tau_B$ for any value τ_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 τ: 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 any time trying to keep E_s completely filled under the constraint i), a uniqe 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 τ_{Min} and the shortest dwelling time n_δ [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 τ_{Min} and n_δ. Note that the limit $\tau \to 0$ is important, because in a time interval with τ=0 smart meters are not needed. In our simulation we mimic the forecast via tests of the alternative

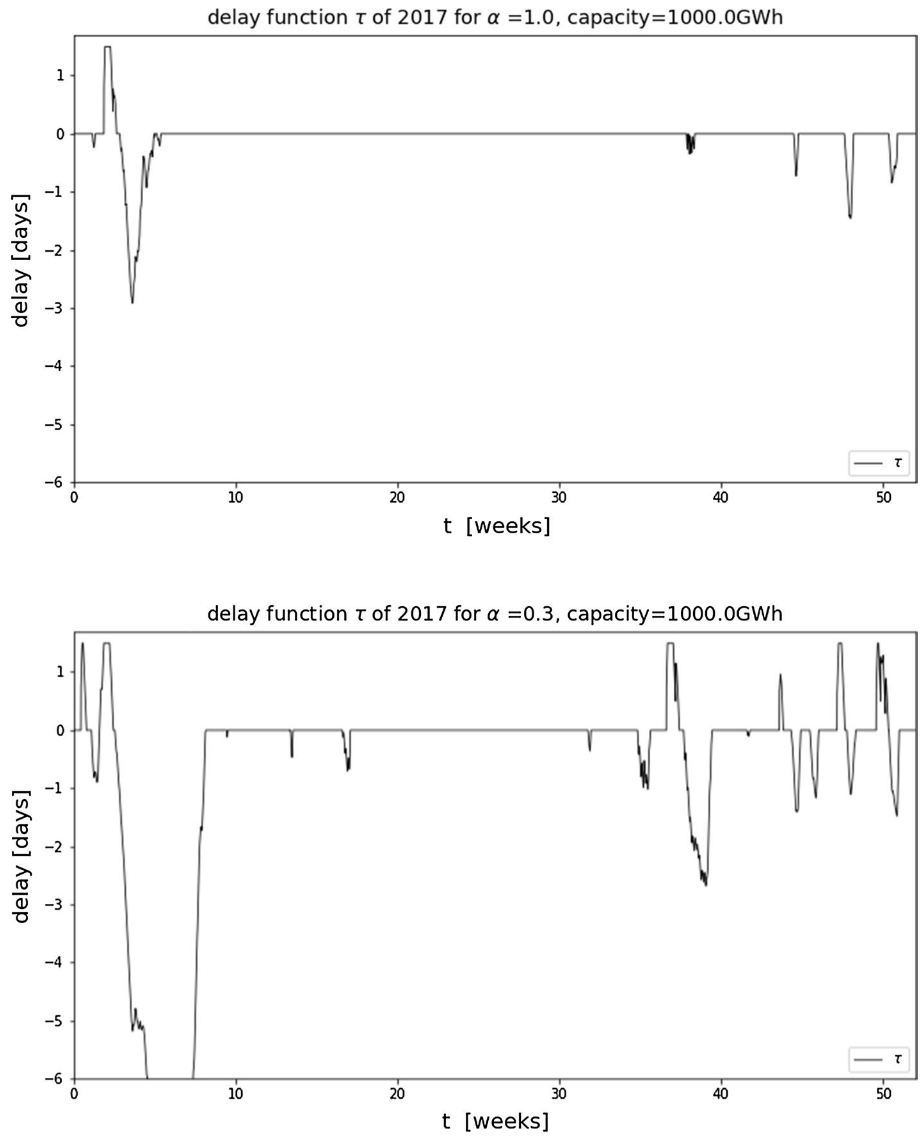

Fig. 2 Delay time τ(t) [days] for the year 2017. Parameters are: $\tau_B = 3/2$ [days], capacity $\varsigma = 1.0$[TWh]. Upper figure: α=1.0, lower figure: $\alpha = 0.3$. Three numbers, $(n_\lambda, n_\delta, n_\sigma)$, characterize τ: the length n_λ [days] of the time-interval, in which τ is moving, the time n_δ [days], during which $\tau < -\tau_B$, and the time n_σ[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

$\tau \to 0$ by successively replacing the upper barrier τ_B with $\tau_{B0} = 0$ for each day and by computing $\tau(t)$ anew. If the new $\tau(t)$ has unchanged τ_{Min} and n_δ, we leave the upper barrier at τ_{B0} for that day, otherwise we move it back to τ_B. In this way we get all the days, in which τ_B is replaced by τ_{B0}. Computing $\tau(t)$ for the last configuration again delivers the days of the year with $\tau = 0$ and therefore all days n_σ with $\tau \neq 0$. Only in the latter case the smart meters are active. A typical delay function τ is shown in Fig. 2. Of particular importance is the interval $[\tau_{Min}, \tau_B]$, in which τ is moving controlled by smart meters. Note that the length n_λ of the interval $[\tau_{Min}, \tau_B]$ is approximately independend of τ_B. (If E_d were a linear function of *t* the approximation would become exact). Therefore we have some freedom of fixing τ_B. Here we set $\tau_B = 3/2$ [days] in most cases. Energy consumption in advance by more than τ_B seems to be awkward. And we know the essentials of the delay function, if we have the three numbers $(n_\lambda, n_\delta, n_\sigma)$ introduced above. Thus we call them characteristic numbers.

The three characteristic numbers of τ are listed in Table 2. Looking at this table we recognize: First, the conditions for wind-solar power are good during the years, except for the years 2015 and 2017. Second, small α-values lead to unsatisfactory results, whereas the influence of the storage capacity ς is less substantial: $\alpha = 1$ and $\varsigma = 1$[TWh] lead to 9 critical days in 7 years whereas $\alpha = 1$ and $\varsigma = 0.3$[TWh] lead to 11 critical days in 7 years. This weak dependence on ς will become important for our conclusions in Sect. 5. Third, it is possible to generate Germany's presently required

Table 2 Characteristic numbers $(n_\lambda, n_\delta, n_\sigma)$, of the delay function τ for 2015–2021

Year	2015	2016	2017	2018	2019	2020	2021
.3 .3	9.6|90|187	5.3|26|184	10.1|46|178	3.6|5|148	3.8|7|163	7.4|29|177	3.3|6|186
.3 .7	9.4|87|151	5.0|22|141	9.9|45|121	3.3|4|99	3.5|4|119	7.2|26|127	3.0|3|133
.3 1.	9.2|85|152	4.8|16|122	9.6|44|109	3.2|2|80	3.4|3|95	6.9|24|106	2.8|3|101
.7 .3	4.7|15|96	2.5|0|84	5.9|23|100	2.2|0|67	2.8|0|62	3.7|3|81	2.0|0|77
.7 .7	4.5|12|70	2.3|0|51	5.6|22|76	1.9|0|45	2.5|0|30	3.4|1|49	1.8|0|37
.7 1.	4.3|9|61	2.1|0|40	5.3|22|66	1.7|0|37	2.3|0|19	3.4|1|49	1.6|0|26
1. .3	4.0|4|67	1.7|0|56	4.9|7|70	1.4|0|49	2.1|0|37	2.0|0|54	1.5|0|46
1. .7	3.7|3|43	1.4|0|28	4.6|6|46	1.1|0|29	1.8|0|19	1.7|0|32	1.3|0|21
1. 1.	3.5|3|39	1.2|0|19	4.4|6|36	0.8|0|22	1.6|0|13	1.4|0|27	1.0|0|14

Left side of first column: α-values. Right side: ς-values [TWh]. Obviously small α values lead to unfavourable results, whereas the influence of ς is less substantial: $\alpha = 1$ and ς =1[TWh] lead to 9 critical days in 7 years, whereas $\alpha = 1$ and $\varsigma = 0.3[TWh]$ lead to 11 critical days in 7 years. n_σ is the number of days, in which the smart meters are active, in our case $n_\sigma \approx 15$ till ≈ 190 out of 365(366) days

electric power by wind-solar power alone, if the conditions are those of the last 7 years and if the consumers are content with smart meters controlling a domain of $[-3/2, 3/2]$ [1] [days].

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 incoming power has to be discarded to prevent increase of τ beyond τ_B or τ_{B0} respectively.

The 'wasted' power arising due to overflow of E_s need not be small at all. In fact, if all possible power is generated, the averaged power amounts to $\approx (1+\alpha) \cdot 60\mathrm{GW}$ (cf. Table 1) and thus the average of 'wasted' power to $\approx \alpha \cdot 60\mathrm{GW}$. 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, in particular for producing 'green hydrogen' by electrolysis, would be an alternative. However, one has to keep in mind that the 'wasted' 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 τ 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 τ_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 α and the storage capacity ς, cf. Table 2. If $n_\lambda \leq 2\tau_B$, everything is fine. If not, then the number n_δ of days, where this inequality is violated, becomes important. n_σ is the number of days, in which the smart meters are active, in our case ≈ 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, 15, 16]. 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 ws_{small}[kWh] on average. However, we do not deal with a small contribution. Instead an average demand of $\approx 60\,GW$ must be met. Following the surplus power approach this demand requires an average production of $(1+\alpha) \cdot 60\,GW$. Therefore, the increase of the running costs is $ws_{small} \to ws_{small} \cdot (1+\alpha)$ and the relative increase is given by α.

4 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 [17], and therefore weak-wind turbines and solar

[1] To deal with the 'critical days' n_δ 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' [14].

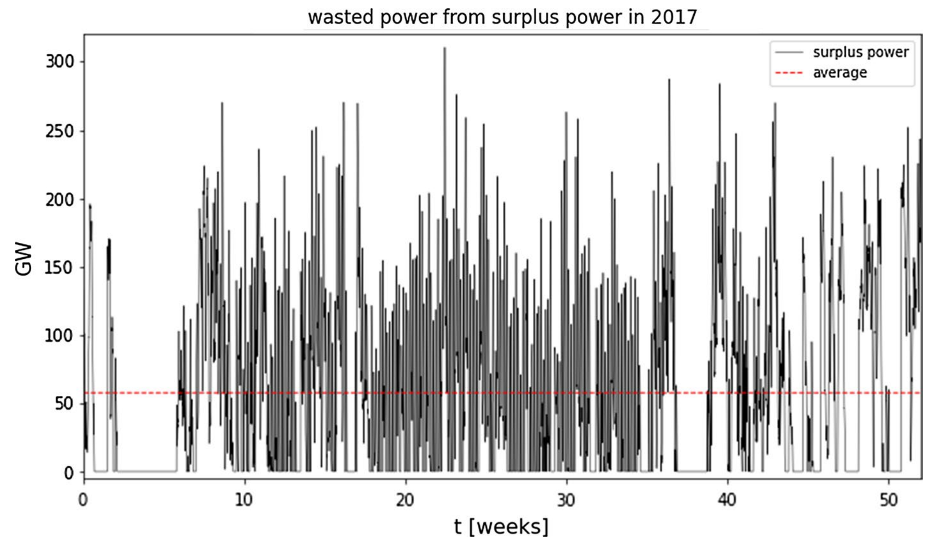

Fig. 3 'Wasted' power. $\alpha = 1$,$\varsigma = 1$[TWh], $\tau_B = 1.5$ days for the year 2017. This power is generated, if the surplus wind-solar devices work all the time generating maximum possible power. (Black) solid line: 'Wasted' power averaged over 1*h*. (Red) dashed line: 'Wasted' power averaged over one year. The averaged value is 57.7 GW. The surplus power has not only sharp high peaks but longer powerless time intervals as well

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 [18] $\sqrt{\beta}$, greater height and consequently higher wind speed enlarged by a factor [19] $(\gamma)^{1/3}$, 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, $P_{low} = 2 \cdot P$. In the high wind regime, however, the power production saturates, since these turbines have a reduced nominal power [19] *P*. This justifies the ansatz

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

Weak-light performance of solar cells [20] depends on the material used [21]. Mono-crystalline PV modules [22], multi junction [23] with selected band gaps and in the future the new generations of DSSCs [24, 25] 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.[2] So we choose for the total surplus power (here denoted as P_{low}) the ansatz

$$\begin{aligned} P_{low}(t) =& P_{nom} \cdot \tanh\left(2P_v(t)/P_{nom}\right), P_{nom} = P_{va} \cdot \eta \\ E_{vlow}(t) =& \int_0^t P_{low}(t')dt' \\ E_d(t+\tau) + E_s(t) =& E_v(t) + \alpha E_{vlow}(t) - E_{dsc}(t). \end{aligned}$$

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

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

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 τ are presented in Fig. 4. Our calculations show the following:

- $\tau_B = 3/2$ [days], $\eta = 1$: τ does not leave the domain [– 3/2,3/2] in all 7 years.
- $\tau_B = 3/2$ [days], $\eta = 2/3$: τ leaves the domain [– 3/2,3/2] only in 2017 for 1.8 days.
- $\tau_B = 1$ [days], $\eta = 1$: τ leaves the domain $[-1, 1]$ only in 2015 and 2017 for 5.6 days in total.
- $\tau_B = 1$ [days], $\eta = 2/3$: τ leaves the domain $[-1, 1]$ only in 2015 and 2017 for 10.1 days in total.

[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.

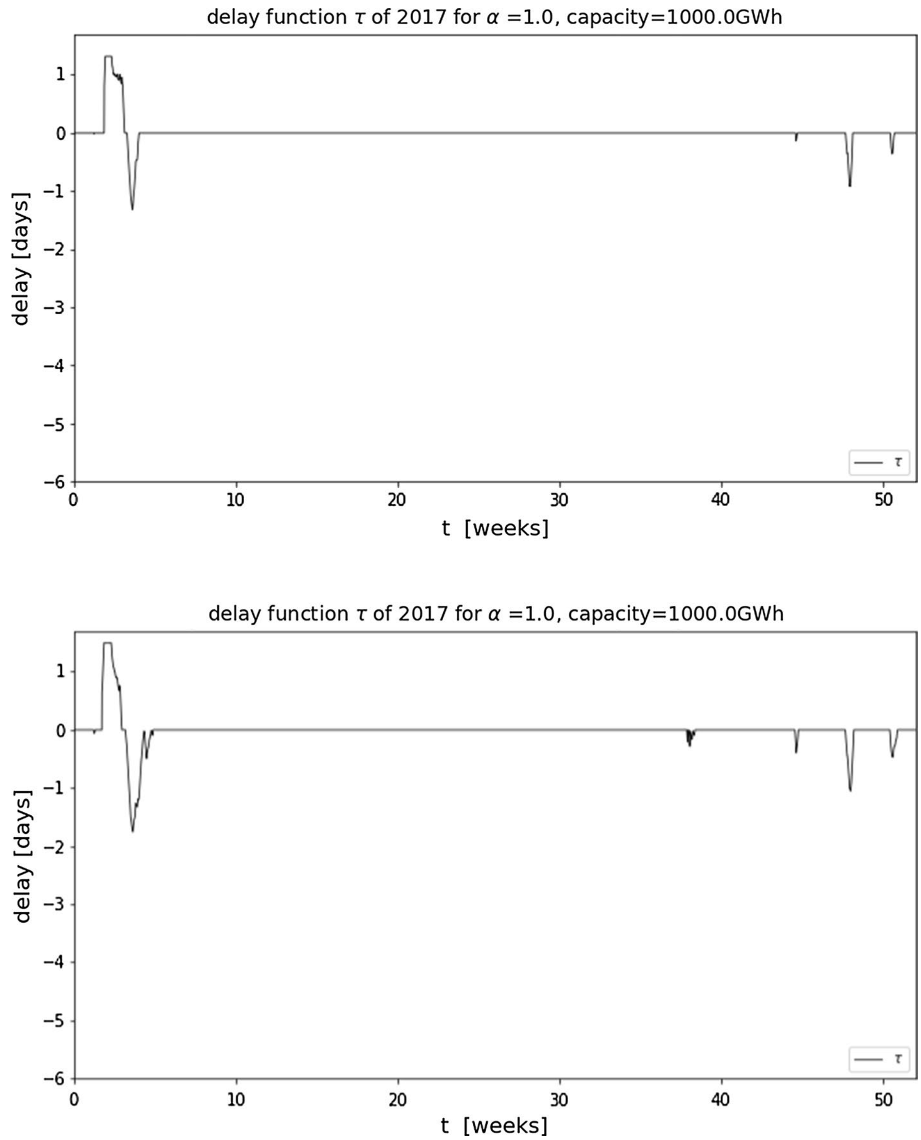

Fig. 4 τ functions, when low-wind and weak-light devices are used. Lower figure: $P_{nom} = \frac{2}{3}P_{va}$. Upper figure: $P_{nom} = P_{va}$. Parameters are: $\alpha = 1$, capacity $\varsigma = 1[TWh]$, year: 2017

The distinctly better outcome for the delay times τ 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

$\alpha = 1, \varsigma = 1\,[\mathrm{TWh}]$ and $\tau_B = 3/2\,[\mathrm{days}]$ we find

$(n_\lambda = 5.3, n_\delta = 22.2, n_\sigma = 72)$. The reason for this disappointing result is the about five times smaller irradiation during the winter months, not compensated by wind power [26].

5 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 $20\% \approx 60\,\mathrm{GW}$ [1, 2] averaged over the year, whereas the total energy production amounts to $\approx 300\,\mathrm{GW}$, (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 2015–21 and were characterized - apart from small waves due to the weekends - by large but slow changes on the summer-winter scale.[3] 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 Sect. 2, leading to a scaling factor of 5. This means that the τ 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 Sect. 3 a storage capacity ς in the range of 1.5–5 TWh will now be required. [4]

Furthermore we can argue that in spite of its enormous volatility at least part of the now huge 'wasted' power can be used for producing 'green hydrogen' by electrolysis and subsequently methane, from which e.g. artificial fuel can be produced 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 100 GW, and the question arises whether this is possible, since the capacity factor of solar cells is dismal for Germany [27–29]: about 10%. First numeric calculations dealing with this question presented unfavourable answers [30]. With continuously increasing power of computer codes taking into account higher levels of details, in particular structures of roofs [31] and facades [28] this question has now been answered convincingly in the affirmative. Smoothing requires another (averaged) ≈100 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 [28].

The needed number of wind turbines is enormous too. Their capacity factor amounts to [29, 32, 33] 25%, meaning that an averaged electric wind power of $200\,\mathrm{GW}$ corresponds to a nominal power[5] of 800 GW. This means 535,000 {135,000} wind turbines of the 1.5 MW {6 MW} type (height 120 m {200 m}) 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+α), $\alpha \approx 1$.

6 Conclusions

In this paper we have analyzed the wild fluctuations of wind-solar power. Using the German electric power data for the years 2015–2021 and scaling the wind-solar power such that the averaged consumption corresponds to the averaged (scaled) wind-solar power we have obtained a realistic picture of the fluctuations during seven years in a combined system, composed of the total electric consumption, of wind-solar power, of storage and of smart meters. We have derived three novel characteristic numbers, describing the volatility of such systems dependent on surplus wind-solar power and

[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 1 TWh.

[5] The capacity factor of offshore wind turbines is larger and amounts to about 40% [29]. But this would become important only, if offshore wind turbines would account for the largest share.

storage. Because of the precise power data for the 7 years 2015–2021 a realistic assessment of the characteristic numbers becomes possible. And with those numbers at hand we get results suggesting: marginalizing the formidable volatility of the combined system is possible, when (i) adding a substantial surplus of wind-solar power (ii) using smart meters[6] [8, 9], (iii) partly selecting different kinds of wind turbines and solar devices. When applying (i)–(iii) the prediction for this system is the following: Marginalizing the volatility will require an electric storage capacity of 0.3–1 TWh only. The prize to be paid will be an $\approx 100\%$ surplus of wind-solar power devices compared to the situation in which only the averaged wind-solar power production matches the averaged power consumption. Based on these results 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 necessarily 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 following our actions described above.

However, no matter how we slice it, the number of required solar cells and wind turbines will become tremendous: Just to satisfy at least the averaged consumption demand, nearly every second roof and possibly a significant part of facades have to be covered with solar cells. Moreover 535,000 {135,000} wind turbines of the 1.5 MW{6 MW} type (height[7] 120 m {200 m}) become necessary. But this arrangement, tremendous, as it is, only succeeds in setting equal the averaged consumption and the averaged wind-solar energy generation. The wild volatility is fully present and marginalizing it requires a challenging effort - the subject of this paper. We offer a successful configuration that does not require much storage capacity. As stated above the price to pay is approximately to 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 outside world 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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Data availability The datasets analysed and/or generated during the current study are available from the author Hans Lustfeld on reasonable request.

Code availability The code has been developed in Python and is available from the author Hans Lustfeld on reasonable request.

Declarations

Ethics approval and consent to participate No ethical approval is required for this research. This research does not require a consent to participate.

Consent for publication This research does not require a consent for publication.

Competing interests The author Hans Lustfeld has no relevant financial or non-financial interests to disclose.

[6] In our calculations smart meters control a domain of $[-3/2, 3/2]$[days] (Sect. 3), and domains down to $[-1, 1]$ [days] (section 4) respectively - with the exception of a few critical (n_δ) days.

[7] The Cologne Cathedral has a height of 157 m.

[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.

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