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DESIGN OF WIND-SOLAR HYBRID POWER PLANT BY MINIMIZING NEED FOR ENERGY STORAGE

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Abstract

An important aspect in designing co-located wind and solar photovoltaic hybrid power plants is the sizing of the energy converters to achieve as efficient power smoothening as possible. In this study, the ratio of wind- and photovoltaic energy converters in a hybrid power plant is determined by minimizing the overall stored energy that is needed to facilitate constant power output. Using Fourier transform the variability is isolated at predefined time scales that are relevant for grid integration. For the investigated time scales, energy and power ratings for energy storages are determined to counteract the variability. The resulting configuration is the one that is able to achieve constant power output with minimum stored energy. It is shown that co-locating wind- and photovoltaic energy converters smoothen seasonal energy generation, and reduce the energy storage need in both the diurnal and seasonal time scales. A case study for south-eastern Sweden is presented where the wind- & solar hybrid plant configuration that minimizes the energy storage need and therefore most closely resembles constant output power is determined. It is found that a ratio of approximately 40-45% wind power in the hybrid power plant yields the lowest need for energy storage. The presented method is valid for any number of co-located energy sources, and can also be extended to sizing of hybrid power systems.

Keywords Hybrid power plant design, Storage aspects, Need for energy storage

1. Introduction

The variable and non-dispatchable nature of wind and photovoltaic (PV) power, driven by atmospheric processes, are one of their biggest power system integration challenges. These fluctuations pose different challenges depending on the time scale that is analyzed, e.g., the deterministic diurnal variability of solar irradiance induces the risk of over-generation and increases the need for flexibility services in power systems with high PV penetration [1]. The seasonal time scale has been shown to be of significance in wind power generation, with an impact on electricity prices in systems with a large amount of wind power [2]. One way of managing the variability is by co-locating different types of renewable energy sources in order the smoothen the output power due to the negative temporal relationship of the underlying atmospheric processes.

Co-locating renewable energy sources to form a hybrid power plant (HPP) has been of growing interest [3]. As the share of variable renewable energy sources in the power system is increasing, co-location is one way of managing the increased variability. The concept of co-locating energy sources to smoothen output power, decrease energy storage need, increase space utilization and lower the financial risks is promising [4]. Most commonly studied HPPs are solar-wind, but many combinations of, e.g., wind, solar, hydro, wave, etc. are found in the literature [5]. Much of the work is focused on assessing and quantifying the complementarity behavior of the energy sources, commonly using correlation coefficients, normally restricted to two sources. In [6] a method was presented to assess the complementarity of three sources using correlation coefficients, later improved in [7]. Other common metrics employed to assess complementarity are e.g. load tracking index, indices based on output fluctuations, and ramp rate assessments [8]. Other studies have evaluated the benefits of co-locating energy sources in terms of reduced physical footprint or higher utilization of electrical infrastructure [9].

An important aspect of HPPs is the sizing of each type of energy converter in the plant. In [10] the shares of wind PV energy converters in a wind-solar-HPP were optimized by finding the combination that met the highest amount of energy demand while maintaining the levelized cost of energy at a level equal to grid tariffs. A similar objective was implemented in [11] where generating-demand matching was optimized using least squares minimization while also including energy storage, and keeping the total cost of the HPP below a defined maximal cost. Another study aimed to find the optimal shares of wind and PV in a wind-solar-HPP assessing the performance using the reliability metric Loss of Load Probability (LLP). The study stated that 40% wind and 60% PV were favorable in terms of energy storage need [12]. Many optimization objectives have been implemented in the literature on the subject of energy converter sizing in

HPPs, most commonly some economical or combination of economical and reliability metric [13]. Examples of reliability metrics employed include LLP, Loss of Load Expected (LOLE), and Loss of Power Supply Probability (LPSP). For assessing the economics of HPPs many have used Levelized Cost of Energy (LCOE) and Life Cycle Cost (LCC) [14].
For renewable energy to be able to replace carbon-intensive energy sources, it is of the essence to increase supply reliability and reduce variability. Due to the intermittent nature of the prime mover (wind, solar, rain) a 100% renewable energy system will need, in some sense, an energy storage system. Energy storages are generally expensive and can be difficult to make profitable. Therefore, we propose that a suitable optimization goal for sizing of an HPP is minimizing the need for energy storage. By finding the combination of PV- and wind energy converters that minimizes the need for stored energy in order to facilitate constant power output, as well as sizing the energy storages needed, we aim to provide a methodology that can help transition renewable energy from intermittent non-dispatchable sources to a reliable energy and power source.

1.1 Aim of the study

This study aims at presenting a novel method of both quantifying complementarity of energy sources and sizing HPPs. Furthermore, the study will investigate the energy storage needs due to variations of varying periodicity of the renewable energy sources. The contribution of this study is twofold:

- Propose an optimization framework for sizing of HPPs
- Analyze energy storage needs considering different time scales

The rest of this paper is structured as follows: in Section 2 we present the metric Need For Energy Storage (NFES) and the data and methodology used. In Section 3 the case study results are presented. Finally, in Section 4 the results are discussed, and in Section 5 conclusions are presented.

2. Data and methodology

In this section, the HPP is defined. Energy converter models as well as the data used to generate power profiles are presented. The optimization framework, filtering of signals, and the case study are also presented.
In this study we consider the HPP to consist of co-located wind turbine generators and PV modules. The wind turbines, PV modules, and energy storage share the same point of common coupling (PCC) where the power is aggregated in accordance with the current definition of a HPP from the IEA Task 50 [15]. Both HPPs located onshore and offshore are analyzed.

2.1 Modelling data

The meteorological data (wind speeds at 125 m above sea level, diffuse and direct solar irradiance) used for generating power profiles were downloaded from the reanalysis dataset Consortium for Small-scale Modeling Retrospective Analysis 6 (COSMO-REA6) [16]. The dataset has a temporal resolution of one hour and a spatial resolution of 6 km. In the study, 15 years of reanalysis data is used ranging from 2004 to 2018. For a detailed description of the model physics and parameterizations, the reader is referred to [17].

2.2 Energy converter modelling

The power generated from the wind turbine depends on the wind speed at hub height and the turbine power curve modeled as in (1).

$$P_{WTG} = \begin{cases} 0 & v < v_{ci} \\ P_r \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} & v_{ci} < v < v_r \\ P_r & v_r < v < v_{co} \\ 0 & v > v_{co} \end{cases} \tag{1}$$

where v is wind speed at hub height, v_{ci}, v_r, c_{co} are the cut-in, rated and cut-out wind speed and P_r is the rated power. In this study specifications of the 5 MW offshore example turbine from NREL [18] with v_{ci}, v_r, c_{co} 3m/s, 11.4 m/s and 25 m/s correspondingly have been used for offshore locations. For onshore locations specifications of a 4 MW reference turbine from NREL [19] with v_{ci}, v_r, c_{co} 3.25 m/s, 9.75 m/s and 25 m/s was used.
The power output of a PV-panel depends primarily on solar irradiance and panel specifications and is calculated according to (2)

$$P_{PV} = \eta_{PV} \cdot A \cdot G \tag{2}$$

where η_{PV} is the panel efficiency, A is the panel area and G is the global horizontal irradiance. In the study a panel area of 2.6 m^2 and efficiency 20.7 % have been used, as for the model JAM72S30-535 [20].
The output power of both wind turbines and PV-panels are in each time step t normalized according to (3) to eliminate the magnitude of power since only the profile of the generated power is of importance for this study.

$$P_{pu,t} = \frac{P_t}{P_{rated}} \tag{3}$$

2.3 NFES

One key aspect of co-locating renewable energy sources to form an HPP is the concept of power smoothing [21]. Metrics based on the correlation coefficients of the co-located energy sources are most commonly used although other metrics have been suggested in the literature [8]. In [22] and [23] HPPs were formed on the basis of minimizing variance, ensuring that the combined variability is lower than the individual counterparts. Variance is a measurement of the spread of data, where the distance of individual points from the mean value is squared. In terms of energy production, deviation from the mean value implies that energy surplus or deficit must be supplied or consumed elsewhere, not the squared value of energy surplus or deficit. In this work, we therefore introduce the metric NFES which is defined as the sum of the differences between actual energy output and mean energy output divided by the total energy output and calculated as in (4) where $\bar{P}, P_i$ are mean power output and power output at time instance i respectively, and Δt is the duration of time step i. The metric NFES represents the fraction of the generated energy that needs to be stored and discharged from an energy storage in order to deliver constant power output.

$$NFES = \frac{\sum |\bar{P} - P_i|\Delta t}{\sum P_i \Delta t} \tag{4}$$

For the case of co-located wind and solar power, (4) may be written as

$$NFES = \frac{\sum |\bar{P} - (x_w P_{WTG,i} + (1 - x_w)P_{PV,i})|\Delta t}{\sum (x_w P_{WTG,i} + (1 - x_w)P_{PV,i})\Delta t} \tag{5}$$

where x_w is the fraction of installed wind power, $P_{WTG,i}$ the wind turbine power output and $P_{PV,i}$ the PV output power. The benefit of co-locating the energy sources can be calculated as in (6) where the reduction of NFES, r, is calculated comparing an HPP and stand-alone installations of equal proportions as in the HPP.

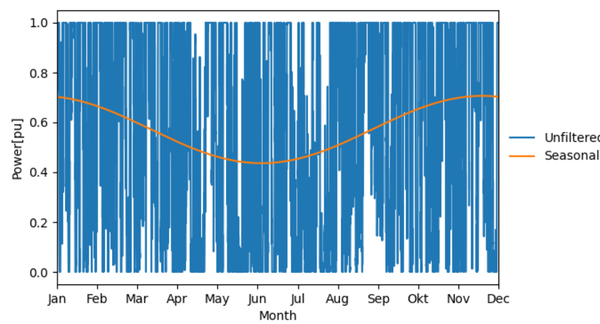
$$r = 1 - \frac{NFES(x_w WTG + (1 - x_w)PV)}{x_w NFES(WTG) + (1 - x_w)NFES(PV)} \tag{6}$$

2.4 Filtering

Sizing an energy storage using hourly resolved data will indeed give information about sizing, although not very detailed. Since COSMO-REA6 is broadcast at hourly resolution, it means that the raw time series contain variability on all other time scales than the hourly. Since the choice of storage type, as well as energy and power capacity, is a direct function of the time scale, the raw hourly signals were separated into frequency components using a fast Fourier transform (FFT) algorithm as proposed in [24]. More specifically, the hourly power output P_i in the time domain can be decomposed into its corresponding frequency domain components using the FFT. After filtering the frequencies of interest, the inverse fast Fourier transform (iFFT) can be used to convert it back to the time domain. In this way, the filtered signal only contains the variability on the time scales of interest. In this study, the time scales were chosen as follows:

1. Seasonal
2. Mid-term
3. Diurnal

The seasonal scale corresponds to filtered signals of frequency with a corresponding period greater than 8 months, diurnal of the period less than 40 hours, and mid-term is chosen to cover the remaining frequencies. The seasonal scale is of interest due to the previously reported negative correlation of wind and solar power [25]. The diurnal scale is chosen because solar irradiation follows a cyclic diurnal pattern following sunrise and sunset. For further discussion on relevant time scales, the reader is referred to [25]. An unfiltered power profile is compared with detrended signals in Figure 1 for the year 2004.



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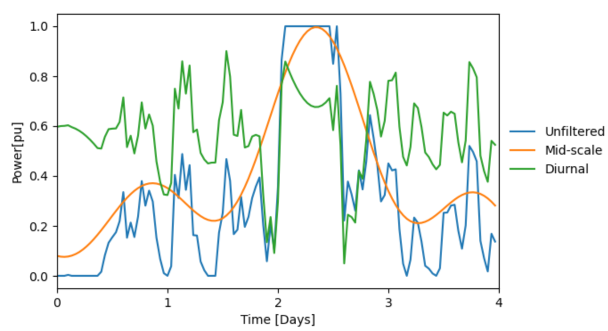

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Figure 1: Example of one sample year (2004) of wind turbine power production detrended to show (a) seasonal and unfiltered power profiles and (b) mid-term and diurnal profiles. Note different time scales on the x-axis.

2.5 Optimization framework

By combining the metric NFES and FFT-filtering, an optimization framework aimed at minimizing the total stored energy as well as providing energy storage capacities is proposed. By minimizing the metric NFES, the share of installed wind power capacity (and therefore also solar power capacity) of which park most closely resembles that of constant power output is determined. The combined output power profile of the HPP where the share of wind energy converters minimizes NFES are then detrended using FFT-filtering and relevant time scales isolated to investigate the energy storage capacities needed for the specific time scale. As discussed in [24], different types of energy storages may be dedicated to handle variations in different time scales. The seasonal variation could for example be handled using pumped hydro and diurnal variation a battery energy storage system. The method is easily extended to include further energy sources, or made to match a desired output power profile. The optimization framework is summarized in the flowchart in Figure 2.

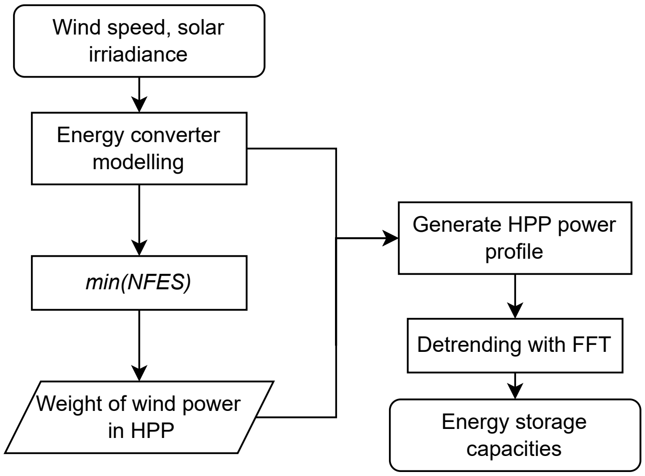

Figure 2: Flowchart of optimization framework

2.6 Gotland case study

The presented methodology is used to size a hypothetical HPP in the surrounding area of Gotland, Sweden located as shown in Figure 3. The area is chosen to include both onshore and offshore locations. The average global solar radiation in the area has an intensity of 117 $\mathrm{W/m^2}$ and annual radiation of 1025 $\mathrm{kWh/m^2}$. The mean wind speeds range from 6.2 m/s to 9.9 m/s in the region, with an average value of 8.9 m/s at 125 m above sea level.

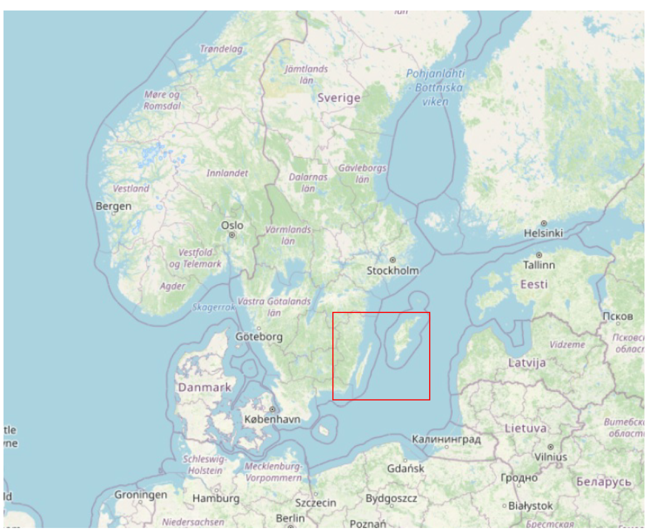

Figure 3: Studied area in red rectangle. Map from [26]

The case study is conducted using reanalysis data spanning from 2004 to 2018 for a time period of 15 years.

3. Results

3.1 Park composition

The share of installed wind power capacity that minimizes NFES for the region of the case study is shown in Figure 4. The share of wind power capacity ranges from $40\% - 45\%$. However, because of the higher capacity factor of wind energy the wind turbine generators produce $68\% - 73\%$ of the total energy production of the HPP.

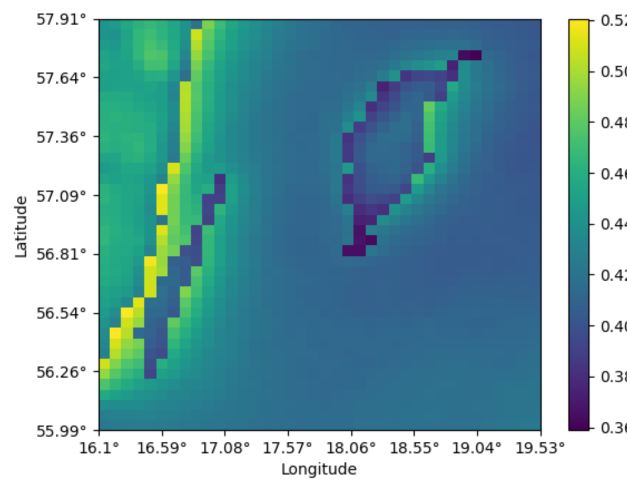

Figure 4: Share of wind power in the HPP

In Figure 5, the binned distribution of installed wind power capacity shares is shown for onshore and offshore locations. To avoid ambiguity only locations clearly defined as onshore or offshore have been considered and coastal regions are not included. There is a small difference that indicates that HPPs located onshore benefit from slightly larger shares of wind power. This is most likely due to stronger negative correlation of wind and PV power onshore, and lower variance of wind power onshore compared to offshore [27]. The higher fractions of wind power onshore correspond to mainland locations, and the lower fractions correspond to island locations where the variance of wind power production is more similar to that of offshore wind power.

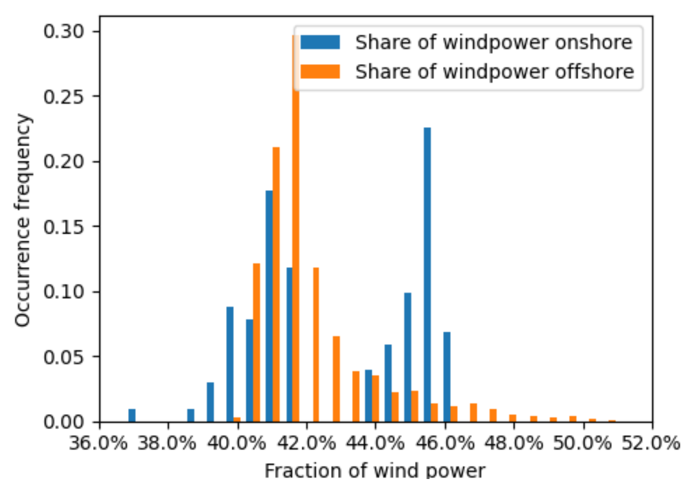

Figure 5: Occurrence frequency of fractions of wind power.

3.2 NFES

The metric NFES is reduced by approximately 40% compared to stand-alone wind- and solar energy converters of the same ratio as the HPP in the unfiltered hourly resolution time scale. In Figure 6 the decrease of NFES is also shown for seasonal, mid-scale, and diurnal variations. The highest reduction of NFES appears when only analyzing seasonal variation. In the diurnal time scale, the reduction is close to the hourly resolution, whereas the mid-scale shows little to no reduction. Figure 6 can also be compared to Figure 7 where correlation coefficients of wind and PV power profiles are calculated. The power profiles of wind and solar energy converters are strongly negatively correlated in the seasonal time scale and show a weak correlation in all other time scales. The reduction of NFES is not entirely motivated by the correlation, as the diurnal NFES are reduced more than for mid-scale variations, despite having a similar negative correlation. In the diurnal scale solar irradiation cycles between maximum and minimum, which means that PV has a relatively high NFES in the diurnal scale. When integrating wind and PV, this heavy cyclic diurnal time scale is reduced and is smoothened by the wind speeds more stochastic diurnal cycle.

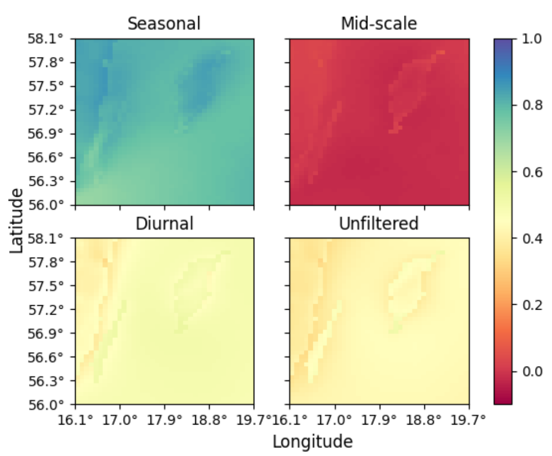

Figure 6: Decrease of metric NFES of filtered profiles

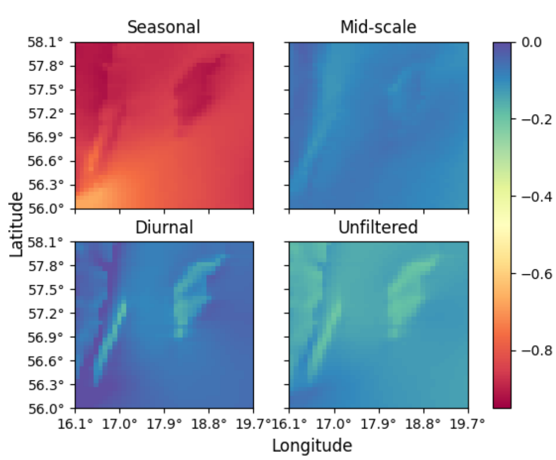

Figure 7: Correlation coefficient ρ of filtered profiles

3.3 Energy storage ratings

Having established to what extent co-locating energy converters influence NFES, in this section the maximum output power and energy rating of the energy storage devices needed will be provided.

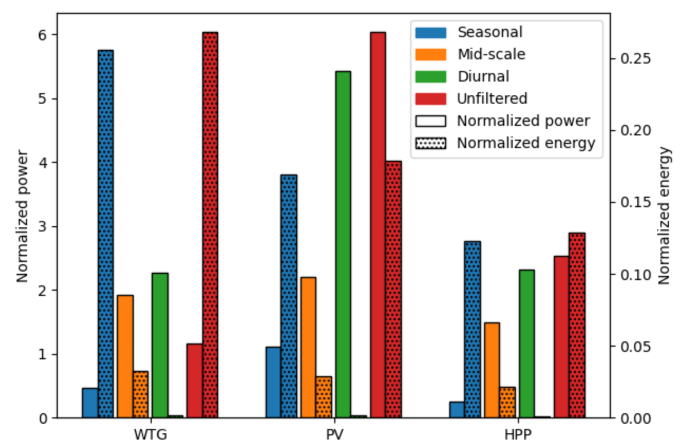

Figure 8: Normalized power and energy ratings

In Figure 8 energy storage sizing is provided in normalized units, where the power rating is normalized by the mean output power of the plant, and the energy rating is normalized by the mean annual energy production of the plant. By normalizing by mean output power rather than rated power, the energy storage ratings are comparable considering a plant consisting of wind power, PV or a wind-solar-HPP with equal annual energy production. *Seasonal*, *Mid-scale* and *Diurnal* are considering separate energy storage systems dedicated to counteracting seasonal, midterm, and diurnal variations respectively whereas *Unfiltered* refers to a single energy storage handling all variations. Energy storages for certain time scales could in a practical example be a combination of for example hydrogen storage, pumped hydro, and battery storage system, which is not further elaborated in this study. The energy storage ratings provided in Figure 8 are indicative of the complementarity in different time scales rather than actual design suggestions of energy storages. Comparing the energy storages needed for an HPP to those of stand-alone installations, all ratings are lower except for the power rating of the stand-alone storage in the unfiltered hourly time scale compared to plant consisting of only wind energy converters.

4. Discussion

In this study shares of wind- and PV-power productions units in an HPP that minimizes the energy storage need are determined using the proposed optimization framework. It is found that 40-45% wind power yields the HPP which most closely resemble constant power output and therefore the minimum NFES, which is similar to previously reported similar studies [12]. The simulated power output from the HPP

is detrended using FFT, and energy storages dedicated to handling the variations in each time scale are sized. On the seasonal time scale, the energy storage need is reduced by 70% due to co-locating, mainly due to the strong negative correlation of the detrended time series. In the diurnal time scale, the energy storage need is reduced by 40% due to co-locating even though the diurnal variations are close to uncorrelated. A stand-alone PV-plant has a high NFES due to a strong diurnal cyclic pattern, whereas wind power in the diurnal cycle is more stochastic, leading to a weaker diurnal cyclic pattern of the HPP power output compared to PV. The NFES in the mid-scale variations are almost unchanged in the HPP compared to stand-alone installations, which implies that the benefits of power- and energy smoothing are strongest in the seasonal time scale, followed by the diurnal time scale.
It is worth noting that sizing energy storages to facilitate constant output power will most likely not be an economically viable option. The presented work suggests a strategy that would eliminate the variability of the power production, but would most probably be unviable for an investor. An alternative approach could be to change the order of the optimization framework as presented in Figure 2 to detrend the output time-series and find the park configuration that minimizes NFES in the diurnal time scale, which in practice would be sufficient to increase certainty in bidding strategies in the intra-day and day-ahead financial markets [28]. The presented storage ratings in this article should be interpreted more as a quantification of the benefits of an HPP in the separate time scales, rather than a suggestion for building an actual HPP.
The results presented in section 3 hold for the studied region, but to conclude that the results are valid in general larger areas need to be covered, and the model needs to be validated, preferably using measurements from an existing HPP.

5. Conclusions

In this article, the share of energy converters in a wind-solar-HPP that minimizes NFES has been studied. Energy storage capacities needed for balancing seasonal, mid-term, and diurnal variations are provided. It is found that between 40-45% wind power in terms of installed power minimizes NFES, with slightly lower shares of wind power in offshore locations. It is shown that the complementarity of wind speeds and solar irradiance significantly lowers the NFES when assessing seasonal variations, and moderately in the diurnal time scale. In the mid-term scale, the benefits of co-locating the renewable energy sources are small compared to seasonal and diurnal time scales.

An interesting extension of this work would be to include further energy sources such as wave energy or tidal energy. It could also be used to size multiple co-located or separately located power plants forming a hybrid power system for larger regional studies.

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