Complementarity assessment of wind-solar energy sources in Shandong province based on NASA

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Abstract: The inherent complementarity of wind and solar energy resources is beneficial to smooth aggregate power and reduce ramp reserve capacity. This article proposes a progressive approach to assess the wind-solar complementarities in Shandong province, China for the preliminary planning of hybrid energy systems. Based on the NASA database, the long-term wind speed and solar irradiation data are obtained and transformed into capacity factors by virtual energy system models. Then, the local assessment that focuses on temporal characteristics is carried out to measure the complementarities in different time scales and search the optimal scale. Progressively, the space scale is extended from a local site to the whole study region and the global assessment is conducted to extract the spatial complementary characteristics. The assessment results are useful to provide the optimal temporal scale and spatial combination of wind-solar complementarity and the proposed approach can be generalised to other regions.

1 Introduction

The renewable energy sources (RESs) are promising alternatives of traditional fossil energy and bring about great benefits. However, the most kinds of RESs are probabilistic, fluctuant, and undispachable, especially for wind and solar energy sources, which causes a strong dependency on energy storage devices and ramp reserve capacities [1, 2]. Meanwhile, thanks to the inherent complementary characteristics of wind and solar energy sources, the aggregate output power of hybrid energy systems is smoothed and so the operation economy can be enhanced [3–5]. Since the degree and efficiency of wind-solar complementarity may vary with the time scale, the determination of appropriate reference scale is essential for the planning of hybrid energy systems. Moreover, the regional hybrid energy system provides more wind-solar combinations and has greater potential than a local one. Therefore, the quantitative assessment of regional wind-solar complementary characteristics is useful and important for the preliminary planning of hybrid energy systems.

The wind-solar complementarity can be estimated by the anti-correlation of corresponding time sequences, so the sample correlation coefficient has been utilised to quantify the characteristics in a future scenario of Sweden [6]. In addition, the statistical probability that the solar irradiation is large and wind speed is small that has been used to describe the scenario of solar complements wind in Australia and vice versa [7]. The 3-year on-site measured data of Ontario in Canada have been processed by percentile ranking and visualised to estimate the wind-solar complementarity [8]. With the utilisation of Monte–Carlo method, the assessment of multi-site complementary characteristics across Italy has been carried out, which concludes that the large-scale monthly complementarity is effective [9]. Moreover, the canonical correlation analysis has been implemented to explore the spatiotemporal balancing of solar and wind energy resources, of which the results show valuable and seasonal wind-solar complementarity in the southern half of Iberian Peninsula [10]. In order to assess the complementarity and availability of wind and solar resources at a candidate site, the virtual hybrid energy system has been established, by which the expected output power is simulated and analysed [11]. Furthermore, the feasibility and technological economy analysis of planned wind-solar hybrid energy system has been performed through the HOMER software [12–14].

As for the complementarity assessment of large-scale wind and solar energy sources, both the temporal and spatial characteristics necessitate to be analysed and so the underlying dataset is not only large but also high-dimensional. The problem of capturing and visualising useful patterns from a high-dimensional dataset is challenging because of the curse of dimensionality. In order to support the preliminary planning of wind-solar hybrid energy systems, the reference time scale where the complementarity is the most cost-effective needs to be determined. In addition, the analysis of spatial complementarities among different sites should be carried out to provide appropriate wind-solar combinations.

Here, the complementary characteristics of wind and solar energy sources in Shandong province, China is assessed quantitatively, and the best time scale and space combinations are analysed for the preliminary planning. A progressive assessment approach incorporating the data process and the analysis of local and global data is proposed to solve the problem step by step and can be generalised to other regions. The long-term meteorological data of the National Aeronautics and Space Administration (NASA) are acquired and transformed into capacity factors. Then, the temporal characteristics of each site is captured and the best time scale is determined in local assessment. Subsequently, the global assessment is performed on the results of local analysis to extract spatial characteristics and search the optimal cross-site complementary combinations.

The rest of this paper is organised as follows. The underlying data are introduced in Section 2. Then, the assessment approach is described in Section 3. The assessment results and corresponding discussion of Shandong province are presented in Sections 4 and 5. Finally, conclusions are drawn in Section 6.

2 NASA data in Shandong province

Due to the high costs and inaccessibility of in situ observation data, the free and easily accessible meteorological reanalysis data become prevalent and are used extensively [15]. The NASA data are produced by the affiliated Goddard Space Flight Centre, which provide the global climate variables spanning from 1979 to present. These reanalysis data are published on a global-gridded basis of 0.5° × 0.67° and at hourly temporal resolution.

The Shandong province is located in 34°22′N to 38°23′N, 114°19′E to 122°43′E. According to the gridded basis of NASA
The NASA wind speeds should be integrated and converted into capacity factors by virtual energy systems and their rated power, which can be expressed as follows [4],

\[ G_w = \begin{cases} 0 & v_m < v_{in} \text{ or } v_o \geq v_{out} \\ \eta_{in} \frac{v_o - v_{in}}{v_{out} - v_{in}} & v_{in} \leq v_o \leq v_r \\ \eta_{out} & v_r < v_o < v_{out} \end{cases} \] (3)

\[ G_f = \frac{H_f A_f \eta_f}{1000P_{ref}} \] (4)

where \( G_w \) and \( G_f \) are the dimensionless wind and solar capacity factors, respectively, and in the range of \([0, 1]\); \( \eta_{in} \) and \( \eta_f \) are the generation efficiencies of WTGs and photovoltaic (PV) panels, respectively; \( v_{in}, v_{out}, \text{ and } v_r \) are the cut-in, cut-out, and rated speeds of WTGs, respectively, m/s; \( H_f \) is the solar irradiation, W/m²; \( A_f \) is the area of PV panels, m²; \( P_{ref} \) is the rated power of PV panels, kW.

### 3.3 Data correction

The data correction is necessitated to be performed, since the reanalysis data are no missing but coarse. The correction factors are used to re-scale the capacity factors [17], which can be expressed as,

\[ F_w = \frac{N_i u_{w,i} G_w}{\sum_{i=1}^{N_i} u_{w,i}} \] (5)

\[ F_f = \frac{N_i u_{f,i} G_f}{\sum_{i=1}^{N_i} u_{f,i}} \] (6)

where \( F_w \) and \( F_f \) are the corrected wind and solar capacity factors, respectively; \( N_i \) is the number of virtual observation sites; \( u_{w,i} \) and \( u_{f,i} \) are the real annual averages of wind and solar capacity factors, respectively; \( u_{w,i} \) and \( u_{f,i} \) are the calculated annual averages of wind and solar capacity factors in the virtual observation site \( i \), respectively.

### 3.4 Assessment indices

The complementary coefficient \( C_i \) is utilised to measure the wind-solar complementarity, which can be expressed as follows,

\[ C_i = \frac{1}{2} \left[ 1 - \frac{\sum_{i=1}^{N_i} (F_{w,i} - \mu_w)(F_{f,i} - \mu_f)}{\sqrt{\sum_{i=1}^{N_i} (F_{w,i} - \mu_w)^2 \sum_{i=1}^{N_i} (F_{f,i} - \mu_f)^2}} \right] \] (7)

where \( N_f \) is the number of capacity factors; \( F_{w,i} \) and \( F_{f,i} \) are the \( i \)th wind and solar capacity factors, respectively; \( \mu_w \) and \( \mu_f \) are the hourly averages of wind and solar capacity factors, respectively. The \( C_i \) is in the range of \([0, 1]\) and the wind-solar complementarity becomes stronger as the \( C_i \) increases. In order to measure the benefit of complementarity, the volatilities of capacity factors of wind, solar, and wind-solar hybrid energy systems need to be quantified consistently. Hence, the variation coefficient is utilised and expressed as,

\[ C_v = \frac{1}{\mu_f} \times \sqrt{\frac{1}{N_f} \sum_{i=1}^{N_f} (F_i - \mu_f)^2} \] (8)

where \( C_v \) is the variation coefficient and the resource volatility becomes smaller as the \( C_v \) decreases.

The composite capacity factors \( F_x \) of hybrid energy systems are represented as the weighted sum of two standalone energy systems and measured by the matching coefficient, which can be expressed as,
where $C_m$ is the matching coefficient and in the range of $[0, 1]$. The improvement coefficient quantifying the benefit of complementarity to suppress fluctuations can be expressed as follows,

$$C_t = 1 - \frac{C_{v, \text{opt}}}{C_{v, \text{opt}} + C_{f}(1 - C_{m, \text{opt}})}$$

where $C_t$ is the improvement coefficient and the benefits of complementarity grows as the $C_t$ increases; $C_{v, \text{opt}}$ and $C_{m, \text{opt}}$ are the smallest variation coefficient of composite capacity factors and corresponding matching coefficient, respectively.

4 Local assessment in Shandong province

Due to the space limitation, the virtual observation site 29 is taken as an example in the local data assessment. The temporal variations of wind and solar capacity factors of site 29 in the 1-month and 1-h scales are shown in Fig. 3. It is clearly seen that the peak and valley values of both energy are asynchronous and the fluctuations are suppressed by wind-solar complementarities.

The power spectral densities of wind and solar capacity factors of site 29 in the semi-log and ordinary coordinates are presented in Fig. 4. From Fig. 4a, the peak values of wind and solar capacity factors appear at the same frequencies. The peak values in 12-, 6-, 4- and 2-h time scales are prominent. In addition, it is clear from Fig. 4b that the solar power mainly distributes in the 12- and 6-h scales and the wind power disperses in the scales larger than 12 h.

The multi-scale quantitative assessment indices of wind-solar complementarities in site 29 are calculated according to (7)–(10), as summarised in Table 1. The anti-correlation of wind and solar energy in 1-month scale has the largest complementary coefficient $C_C$ and is the strongest one among all analysed time scales. With regard to the intra-day scales, the complementarity grows as the scale increases other than the 12-h scale. Since the PV panels generate no electricity in the night-time, the fluctuations of wind power cannot be suppressed and so the wind-solar complementarity in the 12-h scale is the smallest.

The variation trend of complementarities with time scales is also demonstrated in Fig. 5a. Only from the view of point of complementarities, the 1-month scale can be selected as the optimal time scale for the preliminary planning of hybrid energy systems in Shandong province. Furthermore, taking into account the large $C_C$ and power spectral density, the 6-h scale is the most suitable one when confined to the intra-day scales.

The stem plot of the improvement coefficient $C$ and time scale are presented in Fig. 5b. The benefit of wind-solar complementarity grows as the time scale increases other than the 12- and 24-h scales. The 12-h scale is due to the weak complementarity and the 24-h scale is because the dominant fluctuation is transformed from the solar mode to the wind mode.

From Table 1, the benefit of wind-solar complementarity in 1-month scale is also prominent, in which the 40% of fluctuation can be suppressed. As for the intra-day scales, the 6-h scale can be utilised for the preliminary planning. In addition, the overall generation efficiency of WTGs is greater than the one of PV panels and so the matching coefficient $C_m$ should not be too small. Therefore, the 6-h scale is more suitable than the 1-month scale for the planning of hybrid energy systems in Shandong province and taken as the optimal time scale.

5 Global assessment in Shandong province

Based on the analysis results and created temporal attributes of each virtual observation site, the spatial distributions of local wind-solar complementarities in Shandong province are demonstrated in Fig. 6. The reference time scale is set to 6 h, which has been selected as the optimal scale in aforementioned local assessment. It is clear from Fig. 6 that the spatial distributions of complementary coefficient $C_C$ and improvement coefficient $C_t$ are similar and consistent because the two indices quantify the same complementarity from different aspects. The complementary coefficient $C_C$ disperses in the range of $[0.49, 0.57]$ and the improvement coefficient $C_t$ is in the range of $[0.31, 0.40]$. The results reveal that the spatial differentiation of complementarities and necessity of regional resources assessment. Furthermore, the largest five assessment indices and corresponding virtual observation sites are summarised in Table 2. It is obvious that the virtual site 7 and 10 are appropriate for the investment and planning of wind-solar hybrid energy systems, of which the complementary coefficients are $0.5438$ and $0.5356$ and the improvement coefficient are $0.3682$ and $0.3503$.

In order to analyse the optimal cross-site complementary combinations, the spatial complementarities between two different virtual observation sites are also quantified by the complementary coefficient $C_C$ and improvement coefficient $C_t$ in the 6-h time scale. Due to the space limitation, the virtual observation site 29 is taken as an example, of which the spatial complementarities are presented in Fig. 7. It is clearly seen that the distribution patterns of spatial wind-solar and wind-wind complementarities are different.

With regard to the spatial wind-solar complementarities of site 29, the complementary coefficient $C_C$ and improvement coefficient $C_t$ of local wind and regional solar resources are calculated and shown in Figs. 7a and b, respectively. The distribution of spatial wind-solar complementarities is a ribbon pattern. The complementary coefficient $C_C$ disperses in the range of $[0.492, 0.520]$ and the improvement coefficient $C_t$ is in the range of $[0.321, 0.345]$. The results reveal that the spatial complementary combinations can provide more options than local combination. Moreover, the largest five assessment indices and corresponding virtual observation sites are shown in Table 3. It can be seen that the combinations with the virtual site 10 and 19 are appropriate for regional hybrid energy systems, of which the complementary coefficients are $0.5158$ and $0.5119$ and the improvement coefficient are $0.3410$ and $0.3441$. Compared to the results in Table 1, the degree and benefit of spatial complementarities are more prominent than the local ones and the planning of regional hybrid energy systems is rational.

As for the spatial solar-wind complementarities of site 29, the complementary coefficient $C_C$ and improvement coefficient $C_t$ of
Table 1  Results of multi-scale analysis of wind-solar complementarities in site 29

| Scale, h | $C_C$  | $C_{opt}$ | $C_{v,w}$ | $C_{v,s}$ | $C_{m,opt}$ | $C_I$  |
|----------|--------|-----------|-----------|-----------|-------------|--------|
| 1        | 0.5023 | 0.7211    | 0.8416    | 1.4092    | 0.56        | 0.3393 |
| 2        | 0.5027 | 0.7159    | 0.8380    | 1.3896    | 0.56        | 0.3376 |
| 3        | 0.5032 | 0.7082    | 0.8328    | 1.3594    | 0.56        | 0.3348 |
| 4        | 0.5036 | 0.6988    | 0.8258    | 1.3270    | 0.54        | 0.3348 |
| 6        | 0.5072 | 0.6775    | 0.8102    | 1.2626    | 0.52        | 0.3406 |
| 12       | 0.4891 | 0.6203    | 0.7674    | 1.0230    | 0.46        | 0.3149 |
| 24       | 0.5647 | 0.3167    | 0.6755    | 0.3881    | 0.14        | 0.2606 |
| 720      | 0.6380 | 0.1805    | 0.2967    | 0.3033    | 0.32        | 0.4007 |
| 216      | 0.6363 | 0.1444    | 0.2183    | 0.2867    | 0.40        | 0.4162 |

Fig. 5  Stem plots of multi-scale analysis in site 29
(a) The complementary coefficient, (b) The improvement coefficient

Fig. 6  Spatial distributions of local complementarities in Shandong province
(a) The complementary coefficient, (b) The improvement coefficient

Table 2  Largest 5 assessment indices and corresponding virtual observation sites in Shandong province

| Priority | Virtual site | $C_C$ | Virtual site | $C_I$ |
|----------|--------------|-------|--------------|-------|
| 1        | 7            | 0.5438| 7            | 0.3682|
| 2        | 10           | 0.5360| 10           | 0.3619|
| 3        | 11           | 0.5356| 38           | 0.3564|
| 4        | 2            | 0.5328| 2            | 0.3549|
| 5        | 22           | 0.5325| 20           | 0.3503|

Fig. 7  Spatial complementarities analysis of site 29
(a) The wind complementary coefficient, (b) Wind improvement coefficient, (c) Solar complementary coefficient, (d) Solar improvement coefficient
and based on the corrected NASA reanalysis data. In the future, the reanalysis data are processed and analysed step by step. The virtual observation sites are shown in Table 4. It is clear that the combination of the virtual sites 29 and 7 is appropriate for regional hybrid energy systems, of which the complementary coefficient \( C_c \) and improvement coefficient \( C_I \) are 0.5405 and 0.3664, respectively. In contrast to the results in Table 3, the solar resource in virtual site 29 is superior to wind resource, due to better complementarities.

### 6 Conclusion

The complementarity of wind and solar energy resources in Shandong province is assessed quantitatively and the optimal time scale to utilise the wind-solar complementarity from the spatial distributions is conducted on the local assessment. Subsequently, the global assessment that focuses on spatial distributions is conducted on the local analysis results and created temporal attributes to search the potential sites and combinations for hybrid energy systems.

The results indicate that the 1-month scale is the most effective time scale to utilise the wind-solar complementarity from the viewpoint of anti-correlation and fluctuation suppression. As for the intra-day time scales, the 6-h scale is the most effective one and has a suitable wind-solar ratio, which is recommended for planning. Furthermore, the spatial complementary combinations can provide more options and may be more prominent than local ones. So the spatial characteristic assessment and the planning of cross-site hybrid energy systems are significant to make full use of wind-solar complementarities.

The presented wind-solar complementarity assessment is mainly focused on the anti-correlation and fluctuation suppression and based on the corrected NASA reanalysis data. In the future studies, a comprehensive complementarity assessment framework will be established and more precise underlying data will be used.

### 7 Acknowledgments

This paper is supported by the National Key Research and Development Program of China (2017YFB0902800).

### 8 References

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