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The spatial and temporal variation features of wind-sun complementarity in China

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ABSTRACT

Wind and solar energy are two kinds of renewable energy resources with huge potential. Complementarity research between wind and solar resources is quite important for the efficient use of them due to their uncertainty and stochastic volatility. In this paper, the current situation of wind and solar photovoltaic power development in China is firstly introduced. Secondly, the dependence model of wind-sun energy is established by combining copula approach and the Gaussian kernel function, which is a kind of nonparametric kernel density estimation. The copula approach can characterize the dependence structure between the variables so completely that the Kendall's rank correlation coefficient τ calculated from the model above is more accurate. The wind-sun complementarity maps of various regions in China for the whole year and four seasons are further built by using the k-means clustering algorithm with τ as the regionalization indicator. At last, the study analyzes spatial and temporal distribution features of wind-sun complementarity. The results are as following: in spatial dimension of China, Category I ($-0.95 < \tau \leqslant -0.80$) concentrates in the northwest of China; Category II ($-0.80 < \tau \leqslant -0.60$) diffuses in the north, west and a few coastal regions; Category III ($-0.60 < \tau \leqslant -0.30$) is dispersed in the eastern, southwestern and western regions; Category IV ($-0.30 < \tau \leqslant 0.10$) is mostly in the central and southeastern regions. In general, the northwestern and northern regions are more likely to adopt the concept of wind-sun complementarity. In temporal dimension, wind-sun complementarity in spring and summer is superior to that in autumn and winter. The maps have a certain reference significance for renewable resources develop-planning and management in China.

1. Introduction

Renewable resources are certain to play an even more crucial role in the future facing a shortage of fossil energy [1]. Wind and solar photovoltaic (PV) power generation have drawn much attention from many countries as well as China as two major forms [2]. China is a big energy-consumption country [3]. Meanwhile, it has rich renewable energy sources [4]. According to China Electricity Council (CEC), the cumulative installed capacity of wind power is 169 GW. And the cumulative installed capacity of PV power is 77.42 GW by 2016, ranking the first in the world. In the year of 2016, the total installed capacity of electricity in China is 1650 GW. The wind power accounts for 10.2% of the total and PV power accounts for 4.7% [5]. In "Thirteenth Five-Year Plan", Chinese government commits that "the renewable energy sources such as wind and PV power would transform from auxiliary energy to alternative energy". The target of the plan is to make the total installed capacity of the renewable energy power achieve to 750 GW, including 200–250 GW of wind power and 100–150 GW of PV power [6].

There is widespread unpredictability and stochastic volatility for wind and solar resources due to the strong influence of the seasonal climate [7]. Based on that, it is likely to appear the mismatch between wind/PV power supply and the load demand in some periods [8]. Fortunately, the wind and solar resources are naturally complementary in spatial and temporal dimensions [9]. The efficient use of these two energy sources can be achieved through wind-sun hybrid system [10]. So the study of wind-sun complementarity is quite important for the rational energy planning and management.

In the past, the correlation research of two random variables was mainly focusing on calculating the correlation coefficient between variables directly to reflect the degree of their correlation. For example, Cantão et al. [11] calculated Pearson correlation coefficient and Spearman's coefficient directly to evaluate hydro-wind complementarity in the Brazilian territory. When Bett and Thornton [12] studied wind-sun complementarity, they also calculated Pearson correlation coefficient directly, and so on. It is easier and more convenient to calculate correlation coefficients directly, but there are some limitations in this method. For instance, even though the most commonly used Pearson correlation coefficient can reflect the linear correlation, it

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Abbreviations

NPKDE	Nonparametric kernel density estimation
NEA	National Energy Administration
LPSP	Loss of Power Supply Probability
MISE	Mean Integrated Squared Error
MPPT	Maximum Power Point Tracking
CEC	China Electricity Council
CWEA	Chinese Wind Energy Association
CDF	Cumulative distribution function
NHLE	Number of hours lacking electricity
USA	United States of America
PV	Photovoltaic

Nomenclature

$(x_1,x_2,...,x_n)$	sample space
n	sample size
$f(\cdot),g(\cdot)$	probability density function
$F(\cdot),G(\cdot)$	marginal CDFs
h	smoothing coefficient
$K(\cdot)$	kernel function
$f_h(\cdot)$	kernel density estimation
U	normalized wind speed
$C(\cdot,\cdot)$	copula function
τ	Kendall's rank correlation coefficient
$D_k(\alpha)$	Debye function
$H(\cdot,\cdot)$	bivariate CDF
$c(\cdot,\cdot)$	density function of $C(\cdot,\cdot)$
α	relevant parameter in Frank copula
k	degree of freedom
V	normalized radiation intensity

Subscripts

i	index of variable X
F	Frank copula
j	index of variable Y

is unable to capture the nonlinear relationship. Errors may occur if Pearson correlation coefficient is still used when there is a nonlinear relationship between variables [13]. Other correlation coefficients, such as Kendall's coefficient, Spearman's coefficient and Gini coefficient, can reflect the nonlinear correlation between variables to a certain extent, but cannot completely characterize the dependence structure between the variables. Due to the neglect of the study of dependence structure, the direct calculation of correlation coefficient cannot inspect the close relationship between different variables, which will cause deviation from the actual correlation coefficient value [14].

In this paper, the copula method is used as the link function of the marginal cumulative distribution functions (CDFs) of the wind speed and the radiation intensity, to obtain the wind-sun joint CDF. The Kendall's rank correlation coefficient is indirectly calculated to describe the wind-sun complementarity. This method can describe the nonlinear relationship [15]. And more importantly, the copula function has constructed a more accurate and complete correlation structure between the variables based on the actual wind-sun frequency histogram [16], thereby increasing the accuracy of the Kendall's rank correlation coefficient.

Wind-sun complementarity in China has strong nonlinearity. Correlation measure based on the proposed method is unique. It will not change in the linear transformation as well as in any strictly monotonically increasing nonlinear transformation [17]. Therefore, it is more practical, accurate and has quite wide range for applying to each city in China.

To establish the wind-sun bivariate joint CDF by means of the copula approach, their marginal CDFs should be estimated primarily [18]. It is worth noting that China has such a vast territory with big span and various types of climate so that meteorological parameters obey diverse distribution forms. Obviously, it is non-ideal to estimate the marginal CDF with fixed-formed parameter estimation for the above problem. Therefore, the nonparametric kernel density estimation (NPKDE) is adopted here to estimate marginal CDF based on the original sample data, which has the advantage of making no prior assumptions in the distribution form of sample [19]. It has stronger robustness [20].

The methods of defining and measuring wind-sun complementarity usually change with the particularity of different problems, so as to seek for the best solution. In order to study wind and solar resources synergy in Australia, Prasad et al. used the Pearson correlation coefficient to quantify the wind-sun complementarity [21]. Small hydropower is integrated with wind/solar energy to supply power in some mountainous regions of Italy. In order to predict the complementarity between renewable resources, François et al. used a semi-distributed conceptual hydrological model and an index method based on drainage area ratio. The standard deviation of the energy balance was used to examine the complementarity [22]. In order to obtain optimal configuration of wind solar hybrid power generation system while satisfying load power constraints, Chang et al. used parameter method and copula to analyze the wind-solar power correlation, and the genetic algorithm to find optimal result [23]. Hoicka et al. aimed at grid congestion caused by renewable power in Ontario, Canada and studied the wind-sun complementarity under different combinations. The paper found that the combination of solar and wind within locations and between two locations, and also more than two resources and two locations, would serve to "smooth out" power production [24]. Neto et al. proposed a methodology for risk analysis and portfolio optimization of hydro, wind and solar power generation in Brazilian and also discussed the relationship between complementarity of sources and portfolio optimization. The results show that the initial correlation between sources is altered by the cash flow model and mainly by debt. In the diversification process, the complementarity between sources can help reduce economic risk [25]. Chen et al. proposed a fuzzy analytical hierarchical process associated with benefits, opportunities, costs and risks to select a suitable wind-solar power generation project [26]. Considering the particularity of the climate distribution in China, where there is a huge difference between the north and south, coast and inland, NPKDE and copula are adopted to construct wind-solar correlation model in this paper. The obtained Kendall correlation coefficient has stronger robustness, higher accuracy and better generalization.

The article is organized as follows: current status of wind and solar energy sources in China is introduced at the beginning. In the next section, a complete correlation model is built by combining NPKDE and the copula approach and applied to measure the wind-sun complementarity of different regions in China. Subsequently, the K-means clustering algorithm with τ as the regionalization indicator is adopted to draw wind-sun complementarity maps to show its spatial and temporal variation features. In the last section, the internal causes of annual and seasonal results are analyzed in detail. The study has certain reference significance for wind and solar resources management as well as the construction planning of wind/PV power.

2. Current status of wind and solar energy sources in China

China is a large country with a long coastline, rich in solar and wind resources.