Using Analog Ensemble to create optimal wind portfolios

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Abstract

We use the Analog Ensemble (AnEn) method to generate probabilistic 80-m wind power forecasts. Then we use the ensemble spread as a proxy for the degree of difficulty to predict wind power. We further use these generated wind power forecasts to create optimal portfolios of wind installations where each grid point is considered as an individual wind site. These optimal portfolios are created over various spatial scales which enables us to quantify the contribution of different states or regions to optimal wind portfolios. Our results indicate that an optimal aggregation could further increase the potential benefits of geographic smoothing.

Keywords: *Wind power forecasting, Optimal portfolios, Analog Ensemble*

Introduction

We use the Analog Ensemble (AnEn) method to generate probabilistic 80-m wind power forecasts. AnEn provides accurate estimates while requires much smaller computing resources compared to other probabilistic methods. The AnEn enables us to generate wind power forecasts for the whole continental US which we will use to create optimal wind portfolios in order to determine the contribution of different states and regions to various wind aggregation scenarios.

Methods and Results

Our data comes from the NCEP GFS model which is available on a 0.25 degree grid resolution. The AnEn works by taking a deterministic future forecast and comparing it with past forecasts. The model searches for the best matching estimates within the past forecasts and selects the predictand value corresponding to these past forecasts as the ensemble prediction for the future forecast [1, 2]. Our study is based on predicting wind speed and air density at more than 13,000 grid points in the continental US. We run the AnEn model twice: 1) estimating 80-m wind speed by using predictor variables such as temperature, pressure, geopotential height, U-component and V-component of wind, 2) estimating air density by using predictors such as temperature, pressure, and relative humidity. The air density estimates are used to correct the standard wind power curves for different values of air density. We will use the standard deviation of the ensemble members (ensemble spread) as a proxy for the degree of difficulty to predict wind speed. Figure 1 shows how the ensemble spread of 80-m wind speed changes over the continental US.

We use these generated wind power forecasts to create optimal portfolios of wind installations where each grid point is considered as an individual wind site. We define an optimal portfolio as a set of individual wind sites where the portfolio operational risk is minimized for any given level of return. Our methodology is based on Mean Variance Portfolio (MVP) theory where the objective is to find a set of optimum weights for wind sites that minimizes the portfolio risk [3-6]. The risk associated with a single wind site can be quantified by using the standard deviation of the ensemble members. The return, on the other hand, is calculated based on average wind power. Solving the MVP problem for different values of expected return gives us a locus of optimal portfolios where each portfolio is determined by a point in in the risk-return coordinate system, which we refer to as the efficient frontier.

Conclusion

These optimal portfolios are created over various spatial scales which enables us to quantify the contribution of different states or regions to optimal wind portfolios. While geographic aggregation of wind power has been extensively used to reduce wind power output volatility [7-11], an optimal aggregation could further increase the potential benefits of this geographic smoothing. Finally, we use several measures such as Sharpe ratio and HHI to compare these portfolios. Figure 2 shows how optimal portfolios are different based on the spatial scale of aggregation.

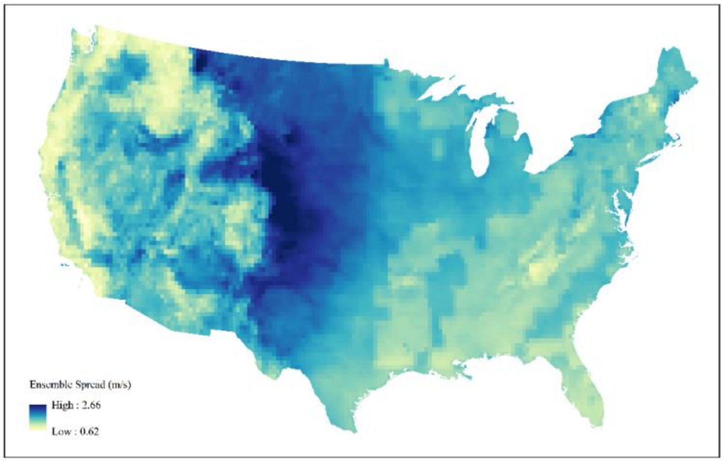

Figure 1- Ensemble spread of 80-m wind speed.

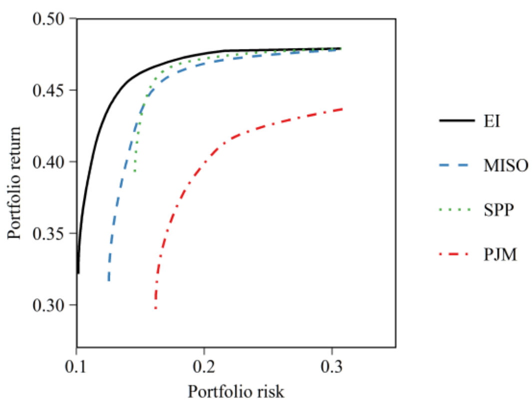

Figure 2- Optimal portfolios in the Eastern Interconnect, MISO, SPP and PJM.

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