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Optimal management of wind and solar energy resources

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ABSTRACT

This paper presents a portfolio-based approach to the harvesting of renewable energy (RE) resources. Our examined problem setting considers the possibility of distributing the total available capacity across an array of heterogeneous RE generation technologies (wind and solar power production units) being dispersed over a large geographical area. We formulate the capacity allocation process as a bi-objective optimization problem, in which the decision maker seeks to increase the mean productivity of the entire array while having control on the variability of the aggregate energy supply. Using large-scale optimization techniques, we are able to calculate – to an arbitrary degree of accuracy – the complete set of Pareto-optimal configurations of power plants, which attain the maximum possible energy delivery for a given level of power supply risk. Experimental results from a reference geographical region show that wind and solar resources are largely complementary. We demonstrate how this feature could help energy policy makers to improve the overall reliability of future RE generation in a properly designed risk management framework.

1. Introduction

Ever since the large-scale commercialization of wind power generation, energy scientists and practitioners have been striving to tackle operational and financial risks entailed by wind generation. The main source of these risks is undoubtedly the lack of predictability about the timing and the volume of the delivered energy output. A certain amount of uncertainty in wind power generation is legitimate, if we think that the output of a wind farm largely depends on the time evolution of weather and climate patterns, which are also partly unpredictable. Contrary to the widespread belief, though, fluctuations in wind power production are persistent and do not significantly scale down with the forecasting horizon. Molloy [19] reports an up to 10% variability in the gross annual production of a reference wind farm, with occasional 20% drops in energy generation from one year to another. Equally large inter-annual changes have been recorded in the aggregate wind power delivery of Spain [13], which can be largely attributed to the dynamics of mesoscale circulation patterns prevailing over the Iberian Peninsula [25]. No matter what the actual source of variability is, production drawdowns of this size deserve special attention as they may have devastating consequences for the financial viability of present and future wind energy investments.

One of the typical solutions recommended in the literature against the adverse effects of wind stochasticity is *spatial diversification*. In simple terms, this means distributing the available capacity over a large geographical area and thus taking advantage of possible dissimilarities in generation profiles. In essence, the decision-maker seeks to develop a network of interconnected energy generation units (*power portfolio*) which could aggregately maintain a sufficient level of power production, even at times when individual components fail to deliver. Spatial displacement as a risk diversification strategy has become a popular topic in the literature; see e.g. the works of Holttinen [12], Archer and Jacobson [2], Cassola et al. [4], Ostergaard [23], Kempton et al. [15], Roques et al. [28], Grothe and Schnieders [9], Santos-Alamillos et al. [30]. Still, the empirical evidence with respect to the true potential of this strategy is mixed.

Cassola et al. [4] report supportive results of the effectiveness of spatial diversification in wind power generation. They demonstrate that a careful redistribution of wind capacity across the isle of Corsica (France) can help reduce the otherwise great variability of local wind resources. In a recent work, Reichenberg et al. [27] present a methodology for assessing the optimal location of wind farms in the Nordic countries to reduce power fluctuations. Their results show a significant dampening of variation in wind energy delivery

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(at the order of 33%) following the adoption of this plan. Similar findings are reported by Archer and Jacobson [2] for the Midwestern United States and by Kempton et al. [15] for offshore areas along the east coast of the country.

Another stream of literature is more pessimistic about the true potential of wind energy for serving base load. Apart from thorny implementation issues often brought up by studies of this group[1], the main reason for the reported poor performance seems to be the fact that most countries, especially those in the central part of Europe, show little spatial variability in wind resources. This is the result of relatively homogeneous weather conditions and low topographic complexity prevailing in these areas. As a consequence, it becomes difficult to find sites with low correlation in generation profiles, which is the key to risk diversification. In one of the early works focusing on the benefits from spatially distributing wind power generation, Ref. [8], ch. 6, estimated that the pairwise correlation of the winds blowing over two randomly chosen sites in Europe diminishes exponentially with distance, with an average decay parameter of 723 km. This means that one would have to look in an approximate range of over 700 km in order to be able to spot two locations with a correlation coefficient as small as 1/3. This finding is indicative of the persistence of weather patterns in Europe and the practical difficulties associated with spatial diversification.

One of the opportunities presented for power balancing on a smaller scales (national or regional) is the chance of supplementing wind generation with in-feeds from other RE resources (such as solar ones). This way one creates a *composite* risk diversification strategy which takes into account not only the smoothing effect of geographical aggregation but also the fact that wind and solar energy typically have complementary profiles[2]. Despite the relatively few research papers on the complementarity of wind and solar resources [10,11,20,29,34], little has yet been said as to how this meteorological pattern can been utilized in the decision-making process—in particular, when it comes to reducing the risk of renewable energy supply.

This paper attempts to fill in this literature gap, by presenting a portfolio-based strategy for the optimal exploitation of wind and solar resources. Power portfolios are optimized not only with respect to the delivered output (as measured by the mean generating capacity[3]) but also with respect to the generation risk (temporal variability in energy production). Mean-variance portfolio-selection has also been recently proposed by Roques et al. [28] for coordinating the deployment of wind energy investments in the European zone. Their examined optimization problem utilizes historical data for the aggregate wind power production of five European countries to deliver an optimal cross-border allocation of wind capacity. Despite the common methodological origin, our work deviates from and extends the previous one in at least two aspects. First, the risk management strategy we examine in this paper goes in two directions: (a) displacing generation units over a large geographical region (*horizontal diversification*) and (b) allocating capacity among technologically heterogeneous power plants (*vertical diversification*). Furthermore, the size of our asset universe is significantly larger. The presented energy planning setting involves some thousands of candidate sites for RE harvesting. An optimization problem of this cardinality poses numerical challenges to known portfolio selection techniques, such as the Critical Line Method (CLM), which has been originally proposed by Markowitz [18] for the solution of mean-variance optimization problems. The Niedermayer and Niedermayer [22]'s implementation of the CLM method, adopted in this paper, allows us to efficiently deal with the computational complexities of such an optimization framework.

The rest of the paper is structured as follows: Section 2 discusses the mean-variance approach to portfolio selection, properly adapted to the case of power production mixes. In Section 3 we present our reference geographical region and provide details on the methodology employed to generate power production scenarios. We also discuss numerical complexities arising from the application of the mean-variance analysis to the particular dataset. Section 4 details the critical line method, which along with the Niedermayer and Niedermayer [22]'s implementation, forms the backbone of our portfolio-selection methodology. Section 5 presents experimental results and Section 6 concludes the paper.

2. Mean-variance portfolio optimization

The Markowitz's mean-variance analysis is the foundation of modern portfolio theory (see e.g. [18,7,16]). This general framework will be subsequently used to derive optimal harvesting plans for RE resources. We assume that the decision maker (energy investor or portfolio manager) owns a certain amount of nominal power and seeks to allocate it optimally between different regions/RE generation technologies so that the following two criteria are met: (1) minimization of the overall energy supply *risk* (expressed by the standard deviation of the generating capacity) and (2) maximization of the aggregate expected *return* (as measured by the average output delivered). The analytical formulation of the optimization problem is given below:

Type-1 formulation

$$\min_{\mathbf{w}=(w_1,w_2,\ldots,w_N)} \quad V_p(\mathbf{w}) \overset{\text{def}}{=} \sum_{i,j=1}^{N} w_i w_j \sigma_{ij} \tag{1.1}$$

$$\text{such that} \quad \mu_p(\mathbf{w}) \overset{\text{def}}{=} \sum_{i=1}^{N} w_i \mu_i = \mu_T \tag{1.2}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{1.3}$$

$$w_i^L \le w_i \le w_i^U \quad i=1,\ldots,N \tag{1.4}$$

$$w_i \in \Re_+ \quad i=1,\ldots,N \tag{1.5}$$

where N is the number of assets (joint wind and solar resources), w_i is the proportion of available capacity allocated at asset i (decision variable), μ_i is the sample mean of generating capacity for asset i, μ_T is the mean return target for the overall portfolio, σ_{ij} is the sample covariance between the generating capacity for i and j. Constraint (1.3) ensures that all available capacity is distributed among the N candidate resources (*budget constraint*), while $w_i^L(w_i^U)$ place a *floor* (*ceiling*) on the proportion of nominal power that can allocated at each asset.

[1] For example, Ref. [28] considers the lack of the network infrastructure for facilitating the transmission of energy between distant power generation units as a main obstacle for the disaggregation of wind power generation.

[2] At mesoscale (regional) level, the variability of the wind and solar resources is closely related. As low pressure centers move over Europe, they bring cloudy conditions while enhancing wind speed. This causes a degradation in solar resources with a simultaneous improvement in winds [29]. The time scales associated with this coupling between solar and wind resources variability are in the range of hours to days while the spatial scales may reach thousands of square kilometers. The temporal aggregation of this variability gives rise to coupled inter-annual variability between the solar and wind resources [25]. Therefore, considerable additional smoothing of power fluctuations may be obtained by combining in an optimal way both wind and solar power technologies.

[3] We make a distinction between the *capacity* of a power plant, which is the ideal (nameplate) power output, and the *generating capacity*, which is the actual energy that is delivered over a specified time frame (see also Section 3.1 and footnote 5).