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Optimal management of wind and solar energy resources

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A B S T R A C T

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.

Keywords: Renewable energy harvesting, Energy supply risk management, Multi-criteria mathematical programming Pareto-optimal set, Markowitz's portfolio theory, Numerical weather prediction.

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 conse quence, 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 dis tributing 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 supplement ing 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 rela tively 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 port folio 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 methodol ogy 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 Nieder mayer [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 frame work 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) max imization 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

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

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

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

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

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

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).

The above formulation is a typical case of a quadratic optimization problem, whose solution depends on the input parameter μ_T. This reflects the portfolio manager (PM)'s yield aspirations. In practice, if μ_T is set above (or below) the maximum (minimum) of $\{\mu_i, \quad i = 1, \ldots, N\}$, the problem becomes infeasible. Hence, the best and worst possible yield on individual assets represent reasonable expectation bounds for the PM. Alternatively to selecting a value for μ_T, the PM can solve the following single objective variant of the above mathematical programming problem:

Type 2 formulation

$$\min_{\mathbf{w} = (w_1, w_2, \ldots, w_N)} \quad V_p(\mathbf{w}) - \lambda \cdot \mu_p(\mathbf{w}) \tag{2.1}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{2.2}$$

$$w_i^L \le w_i \le w_i^U \quad i = 1, \ldots, N \tag{2.3}$$

$$w_i \in \Re_+ \quad i = 1, \ldots, N \tag{2.4}$$

and experiment with the parameter $\lambda \in [0, \infty)$, expressing the trade off between the two objectives (risk and return). The lower the value of λ the greater the aversion towards risk. More details on the solution of type 1 or 2 optimization problems are given in Sections 3.2 and 4.

3. Case study

3.1. Dataset

As a test bed for our portfolio selection methodology, we chose a geographical region of 350,000 km^2 in the southern part of the Iberian Peninsula (see Fig. 1). The region presents some unique characteristics for the study attempted here. First, it has notable wind and solar resources, with about 6 GW of solar[4] and 10 GW of wind installed capacity [26]. In this respect, the region accounts for almost 50% of the world's total concentrating solar power (CSP) installed power [24]. Second, due to the interaction of the mesoscale circulation with the topographic characteristics, this area shows great heterogeneity in wind profiles [30] and a notable pattern of coupled variability between solar and wind resources [29,31].

The Weather Research and Forecasting (WRF) [32] model, quite popular in the numerical weather prediction literature, was used to simulate hourly wind and solar fields for a time period of three calendar years (01/01/2008 31/12/2010) with an average space resolution of 3 km. For each pixel (node) of the reference grid, we calculated the implied *hourly generating capacity factor*[5] that would be delivered by a hypothetical wind farm or concentrating solar power plant. Concentrating solar power (CSP) capacity factors were derived using a parabolic CSP plant model [38], equipped with thermal storage capability equivalent to 7.5 h of nominal power [31]. For the estimation of the wind energy production we resorted to the standard Vestas 3 M turbine model [30]. In order to reduce the computational burden associated with the implementation of the portfolio based approach, generating capacities were first upscaled to a 9 km spatial resolution grid (using bilinear interpolation) and subsequently averaged across each day of the sample period. After excluding offshore areas, we ended up with 2237 candidate nodes for wind power development and an equal number of areas for the placement of CSP generation units. The resulting reference grid is depicted in Fig. 1 (dotted area).

3.2. Practical and numerical difficulties

The application of the Markowitz's methodology to the problem setting considered in this paper poses many challenges from a computational point of view. First is how to derive accurate estimates of the spatiotemporal variability of RE production in such a dense grid, especially when diverse technologies are also taken into account (wind and solar power plants). In our study, this requirement is compromised by employing numerical weather prediction models that are able to quantify the variability of key weather indicators (wind speed, direct solar irradiation, temperature, etc) upon which the production of RE units is dependent. Through the use of the power models discussed in Section 3.1, we can map weather inputs to power generation and thus obtain an indirect estimate of the production co variability for a big array of geographical areas or generation technologies. However, even if one manages to have an accurate representation of the renewable generation at selected nodes of the grid, he/she is still faced with a second challenge: how to incorporate power forecasts into the portfolio selection process.

When having to deal with a large asset universe, most portfolio managers (PMs) would typically apply a heuristic technique to tackle the dimensionality of the problem. In particular, they would split the overall task into two processes. In the first one, briefly termed as *asset selection*, the decision maker tries to spot "promising" combinations of generation sites and technologies which are more manageable in size than the entire basket. After the dimensionality of the feasible set has been reasonably diminished, there follows a *weight optimization* stage, at which the PM decides on the optimal proportion of the overall available capacity that should go to each member of the reduced size array. No matter how straightforward this approach may sound, it often leads to suboptimal portfolio allocations. The main reason is that the selection of assets is typically performed on the basis of site wise assessments and overlooks the correlation structure between generation profiles, which is typically brought out in the second stage of the analysis.

Another source of numerical problems is the fact that the examined mean variance optimization formulations (1) or (2) are parametrized with respect to μ_T or λ, which are both user defined. The set of portfolios arising from varying the value of either of the above continuous parameters is called *efficient frontier,* in the context of Markowitz's analysis, or the set of *Pareto optimal solutions,* in the multi criteria mathematical programming literature. It is important to note that if there were no inequality constraints in the optimization problems (1) and (2), efficient portfolios could be derived analytically using the two fund theorem (see e.g. [16], ch. 6). As long as we put upper or lower bounds on asset weights, we lose analytical tractability and have to resort to a quadratic optimization technique to solve the problem. In this case, in order to get a fine resolution of the efficient frontier, the PM has to repeatedly solve the problem for different values of μ_T or λ, depending on the adopted problem formulation. This can be quite demanding in terms of computational resources, especially when optimization takes place along some thousands of dimensions, as is the case here.

The methodology presented in this paper manages to resolve many of the practical issues mentioned above. First, it avoids the possibility of reaching suboptimal solutions by "attacking the big problem" and, second, it gives the decision maker the opportunity to consistently explore the efficient frontier without having to go through a discretization process. This is a major advantage in

[4] In terms of both photovoltaic and concentrating solar power (CSP) technologies.

[5] The implied generating capacity factor of a site is the amount of energy that would be delivered over a time period if a renewable power generation unit was installed on spot, divided by its nameplate capacity.

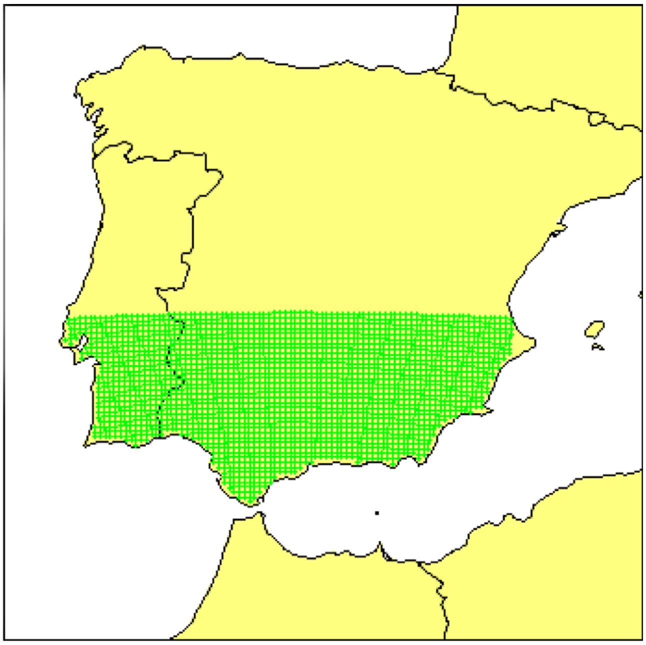

Fig. 1. The geographical coverage of the reference grid of sites used in our study (All maps in this paper -except for that appearing in Fig. 8- were designed using the World Borders Database available from http://thematicmapping.org/downloads/world_borders.php.).

terms of CPU power and storage memory requirements and it is generally achieved by splitting the efficient set in segments where the inequality constraints are inactive for a particular group of assets. The optimal weights for these assets can then be easily calculated using first order optimality conditions. More details are given in the following section.

4. The critical line method

The Critical Line Method (CLM) was initially proposed by Markowitz [18] as a suitable technique for solving mean variance portfolio optimization problems. Later, it was generalised by Markowitz [17] to the context of an "arbitrary" quadratic programming problem with linear constraints. In this paper, we implemented CLM using the Niedermayer and Niedermayer's [22] variant, which makes some smart observations on the structure of efficient solutions and thus avoids unnecessary calculations and inversions of large matrices. In an extensive comparative performance analysis, Niedermayer and Niedermayer [22] show that their implementation of the critical line algorithm manages to reduce significantly the computational burden of the original technique and is also quite efficient for large scale portfolio selection problems when compared to other mainstream optimization methods.

Fig. 2 shows a schematic representation of the algorithm henceforth called CLM NN which is based on the optimization problem (2). More implementation details can be found in Niedermayer and Niedermayer [22]. The CLM NN algorithm starts with the observation that the efficient set is a union of parabolic segments whose edges are defined by the so called "turning points" (see Fig. 2). Every portfolio in the interior of each segment can be found by properly weighting the ones lying on either side. Hence, for representing the efficient frontier with a fine resolution, one does not need to store the weights of all portfolios corresponding to a uniformly spaced grid for the risk aversion parameter (λ); only the "turning points" of the frontier need to be known. This is a major advantage in terms of storing memory and guides the whole evolution of the CLM NN algorithm:

1) Initialization step: find the top edge of the efficient frontier. The initialization step is typically performed by arranging all assets in a descending order of the return (parameter μ) and progressively assigning maximum weight to the best performing ones (the assets lying on the top of the list) until the budget constraint (2.2) is met. The resulting portfolio (maximum return) corresponds to the value λ_0 (as shown in Fig. 2) for the risk aversion parameter.
2) Trace downwards the efficient frontier by finding the next turning point. In the general case, each portfolio of the efficient frontier is composed of two groups of assets: those whose weights lie strictly between the floor and ceiling constraint and those whose weights hit one of the bounds. For an arbitrarily chosen efficient portfolio, some of the $i = 1, 2, \ldots, N$ inequality constraints (2.3) are tight and some are inactive. A turning point occurs when a constraint that was previously tight marginally becomes inactive (or vice versa) when we decrease the value of the risk aversion parameter. Assume that currently the algorithm is at state λ_j of Fig. 2, which corresponds to the underlying efficient portfolio P_j. In order to decide on the next turning point, the algorithm goes through each of the P_j's asset weights and stores the change in the level of the risk aversion parameter when the weight moves to the bound or becomes free. It then ranks all points in a descending order and chooses the one immediately following λ_j (denoted as λ_{j+1} in Fig. 2).
3) Repeat step (2) until you reach the other extreme of the efficient set characterised by the highest risk aversion level (corresponding to the value of λ_K for the risk aversion parameter). This can be alternatively found by progressively assigning maximum weight from the bottom to the top of the μ ranking until the budget constraint (2.2) is fulfilled.

Once the full list of turning portfolios $P_j, \quad j = 1, 2, \ldots, K$ is compiled, the PM is asked to express his/her preference towards return through the input parameter (μ_T). Based on the value of μ_T, the algorithm detects two successive portfolios, P_{j-1} and P_j, $1 \le j \le K$, whose returns encompass μ_T ($\mu_{j-1} \le \mu_T \le \mu_j$). The efficient portfolio P_T that meets PM's expectations is found by linearly interpolating the weights of P_{j-1} and P_j.

5. Experimental results

5.1. *Efficient frontier Wind resources only*

As a first step towards exploring Pareto optimal solutions, we applied the critical line method to trace the efficient frontier corresponding to wind resources only[6]. Fig. 3 shows the resulting curve along with three characteristic points: the *maximum return* (MR), the *minimum coefficient of variation* (CV) and the *minimum variance* (MV) portfolio[7,8]. The MR portfolio is the optimal choice for

[6] The Niedermayer and Niedermayer (2010)'s critical line algorithm has been programmed in Matlab©, by making some major modifications of the original source code provided by the authors (see https://bitbucket.org/afniedermayer/fast_critical_line_algorithm/downloads). Concerning the meteorological database compilation, we have used the R software with the algorithms for the WRF data post processing recommended by the WRF developers.

[7] For a random variable X the coefficient of variation is the ratio of the standard deviation of X over its mean (see e.g. [1]).

[8] Although CLM has been designed to trace the whole efficient set, the only interesting points are those lying above the minimum variance mixing (corresponding to the parabola vertex in Fig. 2). As portfolio theory suggests, no power manager would choose arrays of plants located under the vertex of the curve, as these are "dominated" by the energy mixes of the upper segment. For this reason, the lower segment of the efficient frontier is disregarded from our analysis.

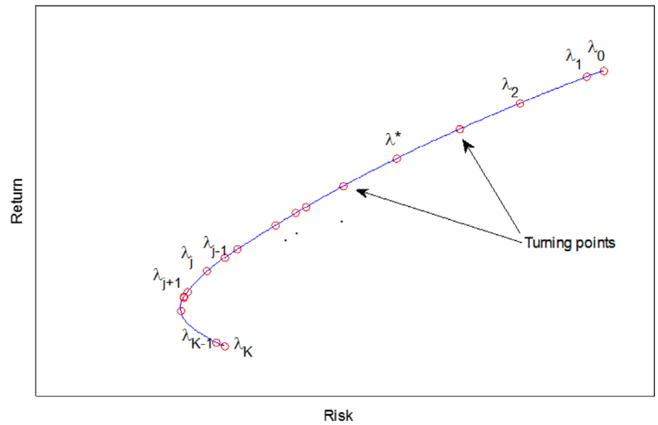

Fig. 2. A sketch of the evolution of the critical line algorithm. Shown is the position of turning points, corresponding to different levels of the risk aversion parameter λ.

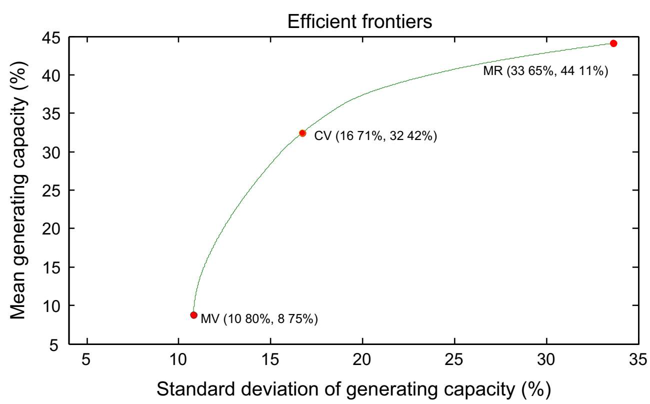

Fig. 3. The efficient frontier resulting from the optimal mixing of wind resources (parallel combinations of CSP plants are not considered).

an investor myopically focusing on maximizing the mean output of a wind farm array. According to Fig. 3, a MR allocation would deliver on a daily basis an average generating capacity of 44.11% (or $44.11 \times 24 = 1058.64$ kW h per 100 kW of installed power) with a standard deviation of 33.65% ($33.65 \times 24 = 807.60$ kW h). The MR portfolio is in fact a rather “edgy” allocation of capacity, as it entails concentrating all available power on a single site[9]. For a fully risk averse investor, the obvious choice is the MV portfolio which manages to bring down the overall daily variability of energy production to 10.80%, albeit with a significant reduction in mean output (8.75% as opposed to 44.11%). CV is the so called *tangency* energy harvesting plan, which attains the best trade off between risk and yield[10]. As Fig. 3 shows, by implementing the CV configuration of wind farms, we are able to attain a risk level for the aggregate generation plan (16.71%) which is almost half its mean generating capacity (32.42%).

5.2. *Efficient frontier The composite case*

Fig. 4 (dashed line) shows the efficient frontier resulting from combining wind and solar resources. For comparison purposes, we also depict the efficient frontier derived from the previous set of experiments (solid line). Note that the two curves overlap in the upper right segment, meaning that wind farm installations are the ideal choice when the objective is the maximization of the average power delivery. Apart from that segment of the curves, the inclusion of solar power units in the asset universe changes the set of Pareto optimal configurations drastically. The risk of the MV portfolio in the composite case goes down to 5.13%, which is almost half the generation standard deviation that can be achieved with wind resources only (10.80%). This risk reduction comes with a substantial improvement in mean generating capacity (20.70% compared to 8.75%), which makes the composite MV portfolio a much more efficient energy harvesting alternative.

The CV portfolio has also superior performance in the composite case. Its coefficient of variation is $5.61/25.49 = 0.22$, which is much more advantageous compared to the best risk reward trade off that could be achieved by spatially distributing wind generation ($16.71/32.42 = 0.52$).

5.3. *Why is it worth thinking in terms of portfolios?*

All portfolios of the efficient frontier are essentially interconnections of power generation units, except for the very “edgy” ones corresponding to high values of λ. An obvious check for the overall efficiency of the Markowitz’s frontier is to plot it against other reasonable production distribution plans or even trivial installations that involve a single site. All these represent competitive alternatives to the decision maker and they are equivalently characterised by a particular yield risk profile (measured by the mean and the standard deviation of the generating capacity, respectively). Fig. 5 shows the results from this exercise. The composite efficient frontier (solid line) is plotted in the same diagram along with each of the 2237 wind farm or CSP candidate sites. Also depicted is the *equally weighted* (EW) portfolio, an otherwise “huge” installation which assigns 1/4474 of the overall capacity to each available wind and solar generation unit. In all areas of the reference grid, solar power generation units could be regarded as more attractive plans compared to the majority of wind farms, as they offer high mean generating capacity with relatively low levels of energy supply risk. Of course, the range of feasible yields for CSP plants is limited and if one pursues an average daily energy output at the order of 30% or above of the nominal capacity, the only available choices are wind farms. An equal mixing of wind and solar resources would deliver an average generating capacity of 21.46% with a standard deviation of 7.66%, which corresponds to a coefficient of variation of 0.36.

As inferred by Fig. 5, Pareto optimal portfolios are far more efficient than both equally weighted and concentrated (single site) harvesting plans. In particular, for the same level of yield offered by the equally weighted mix (21.46%), the PM could alternatively choose the efficient portfolio P_{EW} (located at the left of the EW point), which manages to bring down the overall risk to 5.15% of the generating capacity. This leads to a significant improvement in the coefficient of variation (0.24 compared to 0.36 attained by the EW portfolio).

5.4. *Synthesis of Pareto optimal portfolios*

In principle, one can achieve more Pareto efficient energy harvesting plans by distributing capacity between geographically dispersed wind and solar power generation units. Still, it remains the question of how easy is to implement the suggested efficient portfolios in practice. For instance, if they involve interconnecting some hundreds or thousands of wind farms or CSP plants, environmental or societal concerns could pose a major barrier to the deployment of these plans.

The results from our case study are very encouraging in this respect. In order to address the portfolio size issue, we compiled a list of all sites participating in *any* of the configurations lying on the composite Pareto optimal set. The only condition for a site being included in the list is to receive non zero weight in at least

[9] This is a 9 km-wide area located near the Gibraltar Strait with coordinates (36.1005, −5.6136).

[10] When the decision maker has no particular expectations on yield.

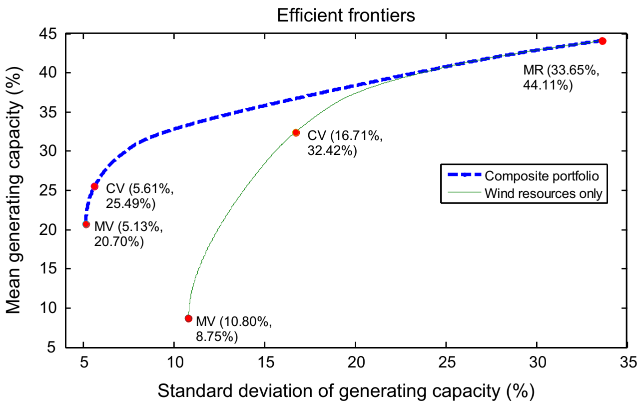

Fig. 4. The efficient frontiers resulting from mixing (a) wind resources only (solid line) and (b) wind with solar energy generation assets (dashed line).

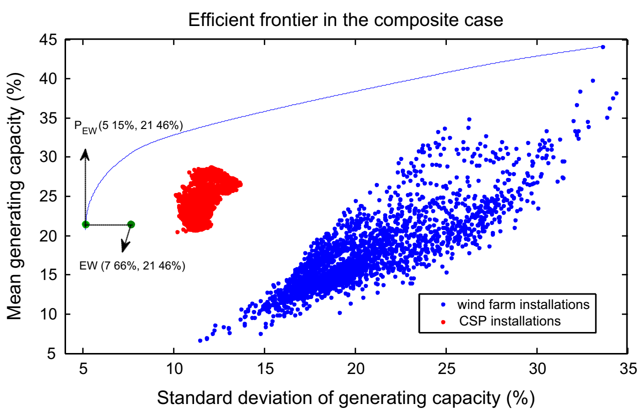

Fig. 5. Performance evaluation of alternative energy harvesting plans. We compare the efficiency of the composite Pareto set (corresponding to optimal combinations of wind/solar plants) with that of single-site installations and an equally-weighted capacity allocation.

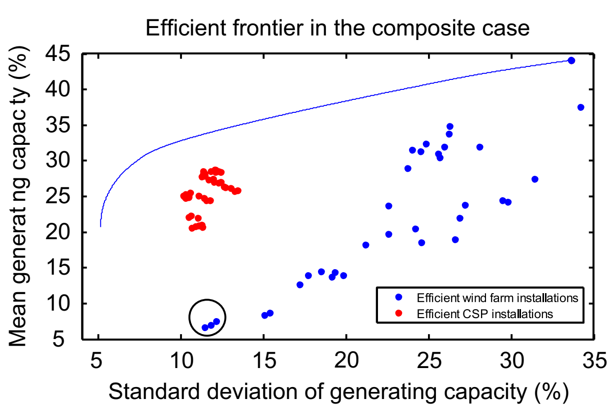

Fig. 6. The synthesis of Pareto-optimal portfolios. Blue (red) dots show the risk–reward relationship of geographical locations which are selected for wind (solar) energy harvesting in at least one of the portfolios of the efficient frontier (solid line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

one of the efficient portfolios. We found that out of the 2237 sites available for wind farm development, only 34 of those are truly necessary. In the case of CSP generation, the number of efficient nodes is also very small (42) compared to the cardinality of the asset universe (also 2237 candidate locations). Fig. 6 shows the positioning of these sites in a mean variance diagram and Fig. 7 shows the true location on the map.

As seen by Fig. 7, most sites are coastal areas combined with carefully chosen continental installations. The reason for the location of most of the wind farm and CSP plant sites is the interaction between the mesoscale atmospheric circulation and the topographic characteristics of the study area (see Fig. 8 and [30]). Most of the time, the mesoscale circulation over the study region is zonal, i.e., wind blows either from the west or from the east. Given the topographic characteristics of this region, when wind blows from the east, wind resources are channeled and increased in the Gibraltar strait area, since it is the only open one, and reduced over the upper Guadalquivir valley. Conversely, when wind blows from the west, wind is channeled by the Guadalquivir river basin, giving rise to strong winds in the upper Guadalquivir valley (Cazorla Mountains in the map). As a result, there is balancing between the wind energy resources in the Gibraltar strait area and the upper Guadalquivir river valley (area enclosed by the red circles; see also [30]). Balancing is perceived in the sense that, if wind farms are located in these two areas, the aggregate wind energy power production will be more stable (the standard deviation of the aggregated wind energy capacity factor will be reduced). Given that: (1) the presented portfolio construction methodology aims at minimizing the standard deviation of the aggregate wind and solar production, and (2) solar resources are characterized by much lower spatial variability than wind resources, the optimal location of the wind farms is mainly conditioned by the wind resources spatial variability, i.e., mostly inside the red circles. The displacement of wind farms and CSP generation units outside these two areas can also be explained on the basis of similar meteorological and topographic arguments. For more details on this issue, see Santos Alamillos et al. [29,30,31].

Fig. 6 gives a clear message as to how indicative are site wise assessments in terms of the true energy potential of the area under consideration. As seen from the graph, there exist assets, such as the encircled wind farm installations at the bottom of Fig. 6, which if examined individually would be probably disregarded as being highly inefficient[11]. However, these installations are to some extent essential for the overall plan, as they supplement other sites in days of low productivity and thus contribute to a overall reduction in the aggregate risk levels.

6. Conclusions

The purpose of this paper was to explore opportunities for power balancing between wind and solar resources. Through a realistic case study involving some thousands of RE sites in the Iberian Peninsula, we investigated the dependence structure of wind and solar fields and proved empirically that, to some extent, they are complementary to each other. We demonstrated how this feature could be utilised in a practical risk management strategy involving optimal mixes of generation sites *and* technologies. Our aim was to provide the whole spectrum of Pareto efficient energy harvesting configurations using as control parameter the portfolio manager's preference towards risk or return.

An important message from this study is that it is generally much more advantageous to think in terms of power mixes rather than single site installations. Apart from the obvious benefits for the minimization of supply risk, site wise assessments are not always indicative of the true potential of each geographical region. Our empirical study has revealed that, an otherwise highly

[11] These particular wind farm installations have the same risk level as many other CSP installations depicted on the graph, although they offer considerably lower return.

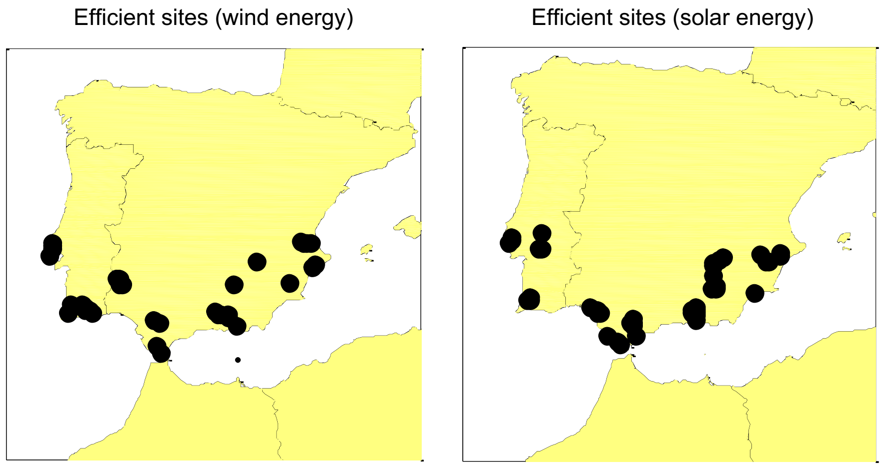

Fig. 7. The geographical location of Pareto-optimal sites in the case of wind and solar resources.

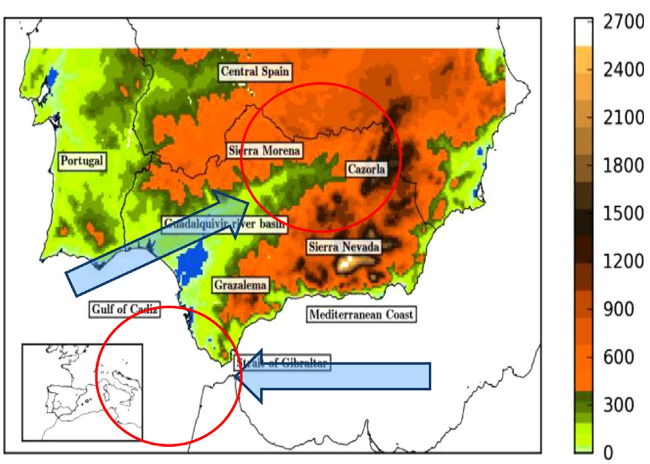

Fig. 8. A geophysical map of the study region, showing the elevation of different areas. Elevation is measured in meters above sea level with reference to a 3-km spatial resolution Digital Elevation Model. The large arrows indicate the two main directions of wind circulation (see also Santos-Alamillos et al. [30], section 2.1).

inefficient location (characterized by high production variability compared to its average delivered energy output) can be a valuable add on to the power portfolio, as it may produce energy in days where other clusters of network nodes underperform.

Overall, our Pareto efficiency analysis points to a more rational and economical exploitation of wind/solar resources. Experimental results have shown that by taking into account dependencies in generation profiles, one is able to make a selective combination of generation sites/technologies that is equally, or even more, beneficial compared to a large scale deployment of renewables. This has important implications in terms of how harvesting plans of renewable energy should be set up in the future.

One of the many directions in which the methodology presented in this paper could be deployed in the future, is to extend the asset universe to a region with larger, possibly Europe wide, coverage. The motivation for this study stems from the principle that the farthest the production sites, the better the opportunities for diversifying away the underlying meteorological/climatological risk. However, the more we extend the geographical scope of the analysis, the higher are also the chances of introducing redundancy in the asset universe, unless one pays attention to select those assets that truly present additional dimensions to the portfolio manager. In this respect, a dimensionality reduction method would be essential (and unavoidable) in order to remove redundancy and bring the number of assets to a manageable size. Diabaté et al. [6] and Zagouras et al. [35,36] demonstrate how cluster analysis techniques can be used in detecting zones of geographical regions with similar solar resources. From a portfolio management point of view, these zones can be treated as individual assets with homogeneous properties, thus allowing for a hierarchical construction of the optimal power harvesting plan[12].

It is also in our future plans to stray from the classical Markowitz framework and derive efficient frontiers with alternative measures of "risk" and "yield". This is a quite active research area in finance (see e.g. the works of De Athayde and Flôres [5]; Jurczenko et al. [14]; Briec and Kerstens [3]), although these techniques have not yet received equal attention as regards the management of energy systems[13]. It is important to note though that most of the alternative risk measures used in the financial literature are typically highly nonlinear metrics of the distribution of portfolio returns. The introduction of these metrics in the objective/constraints part of the problem formulation gives rise to non convex optimization problems that are far more demanding in terms of computational algorithms and resources.

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[12] See e.g. Vijayalakshmi Pai and Michel [33], Zhang and Maringer [37], Murray and Shek [21] for applications of hierarchical portfolio management in the case of financial securities.

[13] Grothe and Schnieders [9] use a non-quadratic measure of risk (Value-at-Risk) in their formulation of the optimization problem. Still, the dimensionality of their asset universe is quite small compared to ours; therefore, the extension of this formulation to large-scale optimization problems is not straightforward.

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