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Optimal wind power deployment in Europe—A portfolio approach

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ABSTRACT

Geographic diversification of wind farms can smooth out the fluctuations in wind power generation and reduce the associated system balancing and reliability costs. The paper uses historical wind production data from five European countries (Austria, Denmark, France, Germany, and Spain) and applies the Mean-Variance Portfolio theory to identify cross-country portfolios that minimise the total variance of wind production for a given level of production. Theoretical *unconstrained portfolios* show that countries (Spain and Denmark) with the best wind resource or whose size contributes to smoothing out the country output variability dominate optimal portfolios. The methodology is then elaborated to derive optimal *constrained portfolios* taking into account national wind resource potential and transmission constraints and compare them with the projected portfolios for 2020. Such constraints limit the theoretical potential efficiency gains from geographical diversification, but there is still considerable room to improve performance from actual or projected portfolios. These results highlight the need for more cross-border interconnection capacity, for greater coordination of European renewable support policies, and for renewable support mechanisms and electricity market designs providing locational incentives. Under these conditions, a mechanism for renewables credits trading could help aligning wind power portfolios with the theoretically efficient geographic dispersion.

1. Introduction

In January 2007 the European Commission brought forward a set of medium-term targets to speed up the transition towards a low carbon economy, including a reduction of 20% of carbon emission by 2020 and an increase of the share of renewables in final energy consumption to 20% by 2020. The power sector will likely bear a disproportionate share of the burden given the limited scope for renewables deployment in other sectors, such that the 2020 target translates into a share of 30–40% of renewables in the electricity generation mix by 2020 (EWEA, 2008a, b). Among the different renewables energy sources, wind power development is expected to account for a large share of the increase in renewable electricity to meet the 2020 target. Wind power has been the fastest growing renewable electricity source over the past years in Europe and accounted for about 4% of the total European electricity demand in 2007 (EWEA, 2008a, b). However, the speed of wind power deployment in the different European countries has been markedly different over the past decade, reflecting different local barriers and different support mechanisms (European Commission, 2005; EWEA, 2006; Finon and Perez, 2007; Faundez, 2008; Fouquet and Johansson, 2008).

There is a large discrepancy in the wind resource across European countries, such that there would be in theory benefits in a more coordinated deployment policy across European countries to encourage investment in the best wind sites. From a system-planning perspective, the issue is, however, complicated by the intermittency and the regional variation in wind generation patterns and the limited integration of the European transmission system. Wind power intermittency has implications both for wind integration costs into the electricity system ("balancing costs") and for the costs associated with maintaining an adequate level of system reliability ("back up costs"). Optimal wind power deployment at the European level should therefore take into account the regional variation in wind power resource and the decreasing correlation between wind farms output as the distance between these wind farms increases.

Conventional investment–planning models lack the capability to represent the intermittent nature of renewables (Neuhoff et al., 2006). Recent research has concentrated on improving wind power investment modelling within a national or regional network by taking into account the variability of wind power and its impact on the electricity system management (Gross et al., 2006; Neuhoff et al., 2006; Short et al., 2003). Such integrated investment-planning models require an extremely detailed representation of the electricity system and they cannot avoid simplifications with current computer processing power. Such integrated models cannot be used for wind power investment planning at the European level given the extra complexity

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Table 1
Evolution of wind power installed capacity from 2001 to 2007 (MW).

Countries	2001	2002	2003	2004	2005	2006	2007
Austria	94	140	415	606	819	965	982
Denmark	2489	2889	3116	3118	3128	3136	3125
France	93	148	257	390	757	1567	2454
Germany	8754	11,994	14,609	16,629	18,415	20,622	22,247
Spain	3337	4825	6203	8264	10,028	11,623	15,145

Source: EWEA, 2008a, b.

introduced by the differences in market design (particularly despatch) and the transmission constraints.

This paper introduces a different complimentary approach to conventional system-planning models to optimise wind power investment portfolios across different countries by taking into account the correlation between wind farms output located in different areas. The Mean-Variance Portfolio (MVP) theory has been used for decades in the financial sector to identify portfolios of bonds or assets which minimise the risk for a given level of profit. The application of MVP to wind power planning provides an analytical framework to optimise the trade-off between maximising wind power output and minimising the variability of wind power output through geographic diversification. The paper uses historical wind production data from five European countries (Austria, Denmark, France, Germany, and Spain) and applies the MVP theory to identify portfolios that minimise the variance of wind power portfolios output for a given level of production. The methodology is then elaborated further to derive optimal *constrained* portfolios for 2020 under a range of constraints including national wind resource potential and transmission constraints.

The rest of the paper is organised as follows. The next session gives some background on the current wind power capacity in Europe and the patterns of wind power production across the different countries considered, using historical hourly wind production data from Austria, Denmark, France, Germany, and Spain for 2006 and 2007. The third section applies the Mean-Variance Portfolio theory to identify optimal wind power portfolios across the five countries based on the patterns of wind power production in the different countries and their correlation. The paper concludes by highlighting some policy recommendations emerging from the analysis.

2. Wind power development in Europe

At the end of 2007, the total installed wind power capacity worldwide exceeded 93 GW and more than half (about 57 GW) was located in Europe. There have been markedly different deployment trends across European countries. Among EU-27 countries, Denmark, Germany and Spain are considered as pioneers for wind energy development. This paper focuses on these three countries together with the neighbouring countries France and Austria which have ambitious wind energy development objectives.

2.1. Wind power development scenarios and the European 2020 renewables targets

Table 1 shows that installed capacity in these five countries has been growing consistently over the past years, despite a slow down in Austria and Denmark in recent years. The differences of wind energy development across European countries can be explained by a variety of economical, technical, and regulatory factors (Agnolucci, 2007). First, the European countries have different wind energy potentials—i.e. different wind resources.[1]

Table 2
Support policies in selected countries.

Countries	Support policies for wind energy
Denmark	Environmental premium+market price
Spain	Either a feed-in tariff indexed on the regulated price for 20 years or a feed-in premium+market price for 20 years
Germany	Feed-in tariff for 5 years at fixed price then 15 years with decreasing tariff
France	Feed-in tariff for 10 years at fixed price then for 5 years the price depends on the capacity factor
Austria	Feed-in tariffs for 12 years at fixed priced (7.6 c€/kWh) with 2 years at a reduced price

Second, regulatory issues and support schemes are critical in explaining the differences in the wind power development rates across countries (European Commission, 2005, 2006). Table 2 summarizes the promotion policies that have been implemented in selected countries.[2] Other factors such as the energy mix, wind energy perception and local opposition, administrative procedures or the transmission grid connection rules also play an important role in explaining the uneven deployment of wind power generation across European countries to date.

The European Commission pointed out the lack of harmonization and coordination for the support mechanisms of renewable energy (European Commission, 2006). This could lead to an ineffective deployment of wind farms across Europe. Wind mills could be built in areas with a poor wind resource but where the support mechanism alone could be sufficient to ensure the profitability of the project. The European directive on the promotion of renewable energy agreed in December 2008 lays down national targets to be achieved by the member states by 2020, which do not take into account the wind resource of the different countries nor the different system costs of such national targets. The Directive incorporates cooperation mechanisms to allow member states to achieve their renewables targets jointly. Member States may transfer renewable energy between each other on a statistical basis, or set up joint projects. But the new Directive does not recognize the Trade of Guarantees of Origin for Member States' renewables target compliance, which could have enabled greater flexibility in meeting the national renewables targets and thereby efficiency gains.

There are many scenarios of wind power development in Europe to 2020, based on different definitions of the theoretical, technical or realizable potentials of wind power (EWEA, 2008a, b; Resch et al., 2008; Tradewind, 2007). The different studies point towards a massive development of wind power generation in Europe over the next decade. Tradewind (2007) proposes three different scenarios for the development of wind power in Europe.[3] Resch et al. (2008) model the development of wind energy using the Green-Net computer model.[4] Table 3 compares the projected

[1] Wind energy that could be withdrawn for wind depends on wind speed and on location topography. For more information: www.windpower.org.

[2] The different types of renewable support schemes include feed-in tariffs, premium schemes, and Green certificates.

[3] The MEDIUM scenario corresponds to the most likely to outcome in the future whereas the LOW and HIGH scenarios correspond respectively to the lowest and the highest "credible" outcomes (Tradewind, 2007).

[4] These scenarios rely on three different definitions of wind power potentials: (i) the theoretical potential, i.e. the upper limit of what can be produced form a certain energy resource from a theoretical point of view without any technical constraints; (ii) the technical potential, defined as the theoretical potential

Table 3
Scenarios of wind power capacity for 2020.

Scenario	Tradewind			Resch et al., 2008
Countries	**Low**	**Medium**	**High**	**Realisable scenario for 2020**
Austria	1700	3500	4900	2074
Denmark	4778	5309	5840	4656
France	23,000	30,000	37,000	24,686
Germany	34,170	48,202	56,640	33,624
Spain	29,653	35,170	40,186	28,322

Source: Resch et al., 2008 and Tradewind, 2007.

development of wind energy capacity (MW) for the five selected countries in these different scenarios.

From a methodological point of view, these scenarios use a "bottom-up" approach by evaluating the potential in each country under a "business as usual" trend or in more ambitious scenarios and aggregating the results at the European level, based on wind resources and technical and policy considerations. In this paper we use a different modelling approach which is not aimed at estimating the potential for wind power development in each country separately but rather at evaluating the potential efficiency gains that could result out of a more coordinated European deployment strategy taking into account the positive effects of geographic diversification on wind output. We use the different countries' wind resource patterns (in terms of output and volatility) as the core feature to determine optimal portfolios among European countries.

Such modelling approach is meant to be complimentary and give new insights on the potential benefits of closer coordination and integration of wind power portfolios across European countries. Our modelling approach echoes the call of the European Commission for greater coordination of renewables development policies across the different member states. There is indeed currently much discussion on which mechanism could be put in place to enable flexible reallocation of the burden sharing across countries, such as for instance a new trading scheme based on guaranties of origin (Neuhoff et al., 2008).

2.2. Optimising the wind resource use and limiting wind portfolios output variability

Wind power production follows markedly different patterns in the different European countries that are illustrated in Fig. 1, based on 2 years of wind power hourly production data (2006–2007) obtained from the Transmission System Operators' websites and wind power installed capacity data from EWEA (2008a, b). The hourly capacity factor of wind power production seems to be much less volatile in larger countries such as Spain, France, and to a lesser extent Germany than in Austria and Denmark.[5] Table 4 shows some descriptive statistics about the mean value of wind capacity factor and its hourly variability based on 2 years of historical data (2006–2007) for the five selected European countries. Denmark has the highest capacity factor mean value while Germany the lowest, and the biggest countries such as Spain, Germany and France have the lowest variability.

At a European level, the optimisation of the use of the wind resource is a multi-facet issue. The wind resource is unevenly spread between countries and within each country (RISOE, 1989). One way to optimise the wind resource use consists in focusing on best sites, where the wind speed is the highest. The second dimension concerns the minimisation of the variability of wind farms' output, which can be smoothed out through geographic dispersion.

Aggregate wind production variability can be reduced by combining weekely correlated wind outputs from different locations. It has been shown in different countries that as the distance between wind farms widens, wind speed correlations between different wind farms falls (Milligan and Factor, 1999; Holtinnen, 2005; Giebel, 2007; Sinden, 2007; Tradewind, 2007; Caralis et al., 2008). For instance, Sinden (2007) found that the hourly correlation coefficient between UK wind farm sites decrease to approximately 0.1 over distances in excess of 100 km. This is primarily achieved through wind power variations in one part of the country canceling out variations in wind power in another part of the country (Drake and Hubacek, 2007).

The combination of wind production patterns in different locations can lead to a wind portfolio production that is more or less variable and with a higher or lower average production. The geographical optimisation of wind farm portfolios can therefore be conceived as a trade-off between two dimensions:

- The search for the best wind resource given that the wind resource is unevenly spread at the inter- and intra-country levels;
- The minimisation of the wind portfolio output variability which can be smoothed out through geographic dispersion at national and/or international level.

Moreover, integrating large proportions of wind energy into electricity systems causes some additional costs from a system perspective. These costs can be roughly separated in two types: "balancing" system costs and "reliability" system costs (Gross et al., 2006). Balancing costs are associated with short-term variability (e.g. hour to hour variation) and the lack of predictability of wind power.[6] Reliability costs are associated with the contribution of wind power to the peak situations and with the corresponding variability of wind power generation during these periods (Milligan, 2002; Giebel, 2005; Gross et al., 2006; Holttinen et al., 2007). When intermittent wind generation replaces conventional generation, an additional installed generation capacity is needed to maintain the same level of reliability (e.g. the same loss of load probability).[7]

3. Applying the Mean-Variance Portfolio theory to identify optimal wind power portfolios

This section applies the Mean-Variance Portfolio (MVP) theory to identify optimal wind power portfolios across Austria, Denmark, France, Germany, and Spain. We first detail the use of the

(*footnote continued*)
constrained by technical boundaries dimensions; and the (iii) realisable potential which represents "the maximal achievable potential assuming that all existing barriers can be overcome and all driving force are active" Resch et al. (2008). Table 3 shows this last scenario which is lower than those from Tradewind (2007).

[5] The capacity factor of a power plant is the ratio of the actual output of a power plant over a period of time and its output if it had operated at full nameplate capacity the entire time. Hourly wind capacity factor is computed as hourly power output figures expressed as a percent of the rated capacity of the wind farm.

[6] High short-term variability increases system costs due to modification in the unit commitment, reserves, and associated system balancing actions (Gross et al., 2006; Holttinen et al., 2007).

[7] A related topic mentioned in the literature is the so-called "capacity credit". The capacity credit is a measure of contribution of wind power installed capacity to the system reliability (i.e. adequacy). As the capacity credit for wind power is never 100%, the replacement of thermal power plants is never one to one and a part of thermal power plant have to be kept functioning to ensure a given level of reliability (Giebel, 2005; Gross et al., 2006).

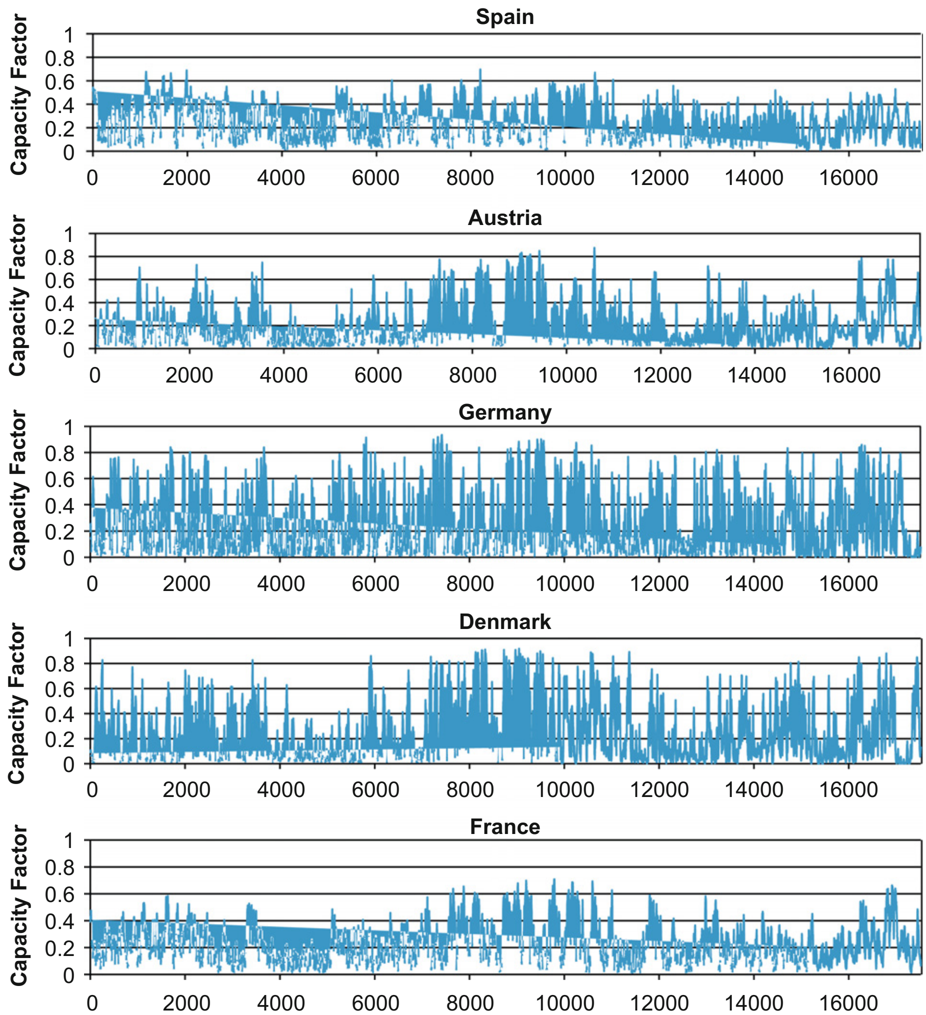

Fig. 1. Selected European countries' wind production patterns (hourly capacity factor from 2006 to 2007).

Table 4
Descriptive statistics of wind power—capacity factors.

	Spain	Germany	Austria	Denmark	France	Actual portfolio 2007
Mean	0.229	0.195	0.229	0.242	0.214	0.212
Standard Deviation	0.138	0.172	0.213	0.218	0.137	0.120

Mean-Variance Portfolio (MVP) theory in the general context of energy planning and then focus on the application of MVP to optimise wind power portfolios. We then use MVP to identify optimal theoretical *unconstrained portfolios* for the five countries considered; we eventually refine the methodology by incorporating a range of constraints to derive optimal *constrained* (realistic) portfolios for the five countries.

3.1. Mean-Variance Portfolio theory and energy planning

Mean-Variance Portfolio (hereafter MVP) theory, based on Markowitz (1952) seminal work, was initially developed for financial securities and has found wide applications in the financial industry.[8] An efficient portfolio is one which has the smallest attainable portfolio risk for a given level of expected return (or the largest expected return for a given level of risk). The process for establishing an optimal (or efficient) portfolio generally uses historical measures for returns, risk (standard deviation), and the correlation coefficients between the different assets to be used in the portfolio.

Portfolio risks and returns are calculated as follows (Elton and Gruber, 1994). The expected return $E(r_p)$ of portfolio P containing N assets i (expected return r_i, standard deviation σ_i) in proportion X_i is simply the weighted average of the N assets expected returns:

$$E(r_P) = \sum_{i=1}^{N} X_i E(r_i).$$

The portfolio standard deviation σ_p is defined by the following formula:

$$\sigma_p = \sqrt{\sum_{i=1}^{N} X_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j},$$

[8] See e.g. Elton and Gruber (1994) and Fabozzi et al. (2002) for a recent review of the developments of the Portfolio theory.

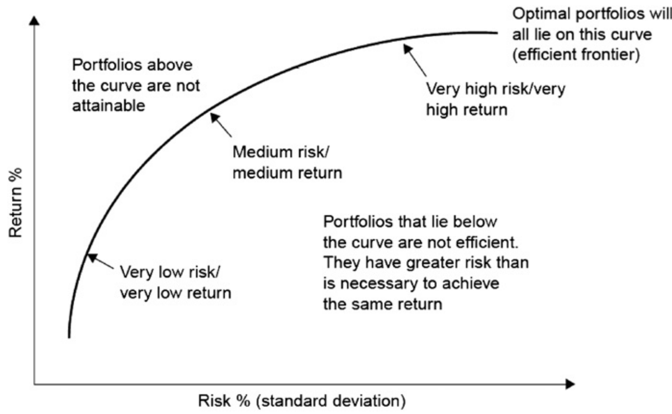

Fig. 2. Efficient frontier for a portfolio of two risky assets.

where ρ_{ij} represents the correlation between the returns r_i and r_j of the two assets.

As Awerbuch and Berger (2003) explain, by computer processing the returns, risk (standard deviation of returns) and correlation coefficients data, it is possible to establish a number of portfolios for varying levels of return, each having the least amount of risk achievable from the asset included. These are known as optimal portfolios, which lie on the *efficient frontier*. Fig. 2 shows the efficient frontier for a portfolio of two risky assets. Optimality refers to Pareto optimality in the trade-off between portfolio risk and portfolio return. For each portfolio on the efficient frontier:

- The expected portfolio return cannot be improved without increasing expected portfolio risk.
- The expected portfolio risk cannot be reduced without reducing expected portfolio return.

The investor then simply has to choose which level of risk is appropriate for their particular circumstances (or preference) and allocate their portfolio accordingly. In other words, the MVP theory does not prescribe a single optimal portfolio combination, but a range of efficient choices.

The MVP method can be applied to determine the optimal portfolio of generation plants either for a country or a particular company. Bazilian and Roques (2008) provide an overview of the recent research applying MVP to energy planning. Most applications of MVP to optimising power generation have taken a *social welfare maximisation* perspective, aiming to minimise generation cost for each risk level, and concentrating on risky fossil fuel prices (Awerbuch, 2000, 2005). Based on projected unit costs and volatility covariation patterns, such studies determine "efficient" (Pareto optimal) portfolios of generating assets.

Bar-Lev and Katz (1976) pioneered the application of the MVP theory to fossil fuel procurement in the US electricity industry, and found that generally the US electric utilities are efficiently diversified, but that their portfolios were generally characterised by a relatively high rate of return and risk, which they interpreted as being a consequence of the 'cost-plus' regulatory regime encouraging utilities to behave in a risky way. Humphreys and McClain (1998) and Awerbuch (2000) evaluated the US generation mix and showed that adding fixed-cost renewables to a portfolio of conventional generating assets serves to reduce overall portfolio cost and risk, even though their stand-alone generating costs may be higher. Awerbuch and Berger (2003) used MVP to identify the optimal European technology mix, considering not only fuel price risk but also O&M, as well as construction period risks, while Jansen et al. (2006) used MVP to explore different scenarios of the electricity system development in the Netherlands. Finally, Roques et al. (2008) applied the portfolio theory from a private investor perspective to identify optimal portfolios for electricity generators in the UK electricity market, concentrating on profit risk rather than production costs risk.

3.2. Applying Mean-Variance Portfolio theory to wind power deployment

In the context of wind power investment planning, the MVP theory appears as a well suited tool to optimise the trade-off between maximising wind portfolio output and minimising wind portfolio volatility. Wind power portfolios can be optimised following different objectives; each objective corresponds to a different trade-off between "return" and "risk". The existing literature applying MVP to wind power portfolios has used different definitions of portfolio risks and returns. Drake and Hubacek (2007) analyze geographical wind power portfolios for four zones in the UK. They construct optimal portfolios that maximise wind power generation and minimise total variance. Milligan and Artig (1998), Hansen (2005), and Datta and Hansen (2005) applied the portfolio theory to find "geographic" portfolios in different regions of the US. In these papers portfolios are optimised in order to maximise "reliability" i.e. maximising wind power production and minimising variance during peak-hours. In all these papers, the combination of wind production from sites with low or negative correlations is the main driver of wind portfolio optimisation through geographic diversification.

In this paper we use successively two objective functions to define optimal cross-countries wind power portfolios: (i) "*Optimising wind power output*" which consists in maximising wind power production and minimising hourly variability at all times; and (ii) "*Maximising wind power contribution to system reliability*" which consists in maximising wind power production and minimising variability during peaking-hours.

Depending on the objective function considered, we use the following variables to quantify the wind portfolio "return" and "risk":

(i) *Optimising wind power output*. In this case we build wind portfolios considering short-term variability. We determine "optimal" portfolios (i.e. the percentage of wind power installed capacity in each country) that maximise wind production per unit of installed capacity (capacity factor) and minimise "hourly" variations. Contrary to e.g. Drake and Hubacek (2007), we do not use the "anachronic" variance of the wind production computed from data time series directly, but rather the variance of the hourly variation of wind production ($P_t - P_{t-1}$). Such approach is motivated by the choice to take into account only the temporal hourly variation of wind power output and not anachronic variations (Boccard, 2009).

(ii) *Maximising wind power contribution to system reliability*. In this case we limit our study to wind power data corresponding to peak demand hours (defined as 10% of the highest total demand). Then we construct portfolios that maximise the wind power production per unit of installed capacity (capacity factor) and minimise the variance during peak-hours. This can be interpreted as an assessment of the contribution of wind power to the system adequacy or a maximisation of portfolio capacity credits.[9]

[9] As demonstrated in Gross et al (2006), the reliability measured with the loss of load probability (LOLP) depends on the variance of the system "margin" (defined as demand minus total available generation, including wind power).

Table 5
Wind power capacity factor data for objective no. 1 ("Optimising wind power output").

	Spain	Germany	Austria	Denmark	France
Mean	0.229	0.195	0.229	0.242	0.214
Standard deviation (hour to hour, $P_t - P_{t-1}$)	0.016	0.019	0.048	0.027	0.017
Correlation coefficients					
Spain	1.000	−0.033	0.011	−0.061	0.062
Germany		1.000	0.045	0.362	0.147
Austria			1.000	0.005	0.010
Denmark				1.000	0.046
France					1.000

Wind power output variance is computed from hourly wind power production data for Austria, France, Germany, Spain and Denmark for the years 2006 and 2007.[10] These hourly data are indexed with the same time reference system. For each country data is normalized using installed capacity in order to compute hourly capacity factors.[11] This allows us to work independently of installed capacities. Hourly demand data by country for the years 2006 and 2007 are used to determine peak-hours and the corresponding wind power production during these peak-hours.

In the following sections optimal portfolios of wind power installed capacity for today and 2020 are computed and compared with current and projected wind power portfolios for the five countries considered in European scenarios. As wind power has different patterns in the five countries, weighting the installed capacity across the five countries in different ways results in cross-countries wind portfolios with different average capacity factors and different levels of output variability. One important assumption here is that there is no restriction on the weight of the different countries in the wind portfolios and that production patterns develop homogenously to current levels.[12] The Section 3.3 builds optimal *unconstrained* theoretical portfolios without any exogenous constraint, while the Section 3.4 incorporates country wind resource potential and transmission constraints to model more realistic *constrained* portfolios.

We finally want to point out that our methodology does not take into account a number of important regulatory and market frameworks issues which are critical for wind power investment decisions, such as grid access conditions, balancing market design, or support mechanism. The objective of this paper is to demonstrate the use of MVP theory as an insightful analytical approach to take into account the impact of wind output variability and correlations of wind output across different locations within a wind farm portfolio. The extension of the simple modelling framework presented in this paper to take into account other investment-planning issues and constraints is left for further research.

3.3. Optimal unconstrained portfolios

In this section *unconstrained* theoretical optimal portfolios for wind power are computed and compared with current and projected European portfolio for 2020 (using the scenarios from Resch et al., 2008 and Tradewind, 2007 medium scenario as references). Optimal portfolios are constructed successively following the two different objectives introduced in the previous subsection. For each objective, we construct the efficient frontier by computing the range of optimal portfolios that maximise wind power "return" (defined as the average capacity factor) and minimise wind power "risk" (defined as the standard deviation of wind output variation).

3.3.1. Objective no. 1: optimising wind power output

Table 5 presents some descriptive statistics of the data used to compute optimal portfolios, based on 2 years (2006 and 2007) of hourly data. Denmark, Spain and Austria have the highest average capacity factors, while Spain and France have the lowest hourly output variability.

Table 5 also reports the correlation coefficients between the hourly variations of wind production across the five countries. Correlation coefficients are important because combining two wind power output patterns that are less correlated (or correlated negatively) yields a portfolio with less total output variability. Hourly variations can be more or less correlated depending on the geographic location of each country and the corresponding wind fronts. For instance neighbouring countries usually have positive wind hourly variations correlations (e.g. Germany and Denmark or Germany and France), while remote countries present low or negative correlations (e.g. Spain and Germany). Low or negative correlations between the wind output of different countries indicate that there exists a potential to reduce wind portfolios output hourly variability (or to increase the average production for the same level of output variability) by spreading wind power capacities over several European countries.

Fig. 3 shows the theoretical efficiency frontier for wind power portfolios in the five countries considered. The optimisation model computes the minimum standard deviation (portfolio risk) for any given level of average power generation (portfolio return). Once the risk and return of a range of portfolios have been computed, an efficiency frontier is constructed. The efficiency frontier illustrates those combinations of portfolio output and output standard deviation that are possible by varying the proportion of each country's wind capacity in the cross-country European portfolio. Any point located along this frontier represents a combination of wind capacity across countries that minimises wind output standard deviation for any given level of average portfolio power output.

Fig. 3 provides a number of interesting insights. First, the current wind power portfolio in the five countries considered does not belong

[10] Wind production data were collected from the transmission system operators or distribution system operators. The authors gratefully acknowledge OeMAG, REE, and ERDF for providing historic wind power time series for Austria, Spain, and France respectively. Data for the other countries were obtained from the following TSO websites: Denmark: Danish TSO Energinet (www.energinet.dk); Germany: SouthWest German TSO ENBW (www.enbw.com); NorthWest German TSO RWE (www.rwetransportnetzstrom.com), North German TSO EON (www.eon-netz.com); Eastern German TSO Vattenfall (www.vattenfall.de).

[11] As there is no available data about wind power monthly/weekly installed capacity, we use linear variation of wind power installed capacity using yearly statistics (EWEA, 2008a, b).

[12] This assumption could be supported by the idea that the repowering of current wind farms will account for a considerable part in the increase of wind power capacity in 2020. However, off-shore wind power capacity will likely represent a growing share in the future and current data does not account for this production pattern.

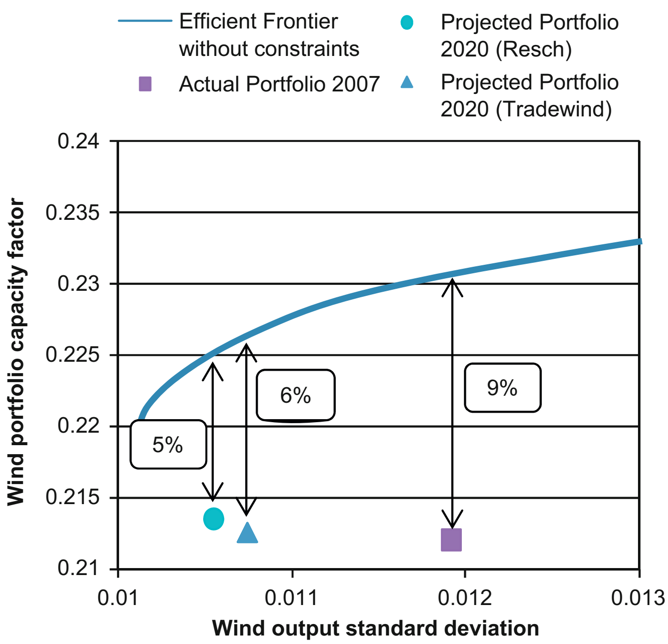

Fig. 3. Unconstrained efficient frontier—objective no. 1 ("Optimising wind power output").

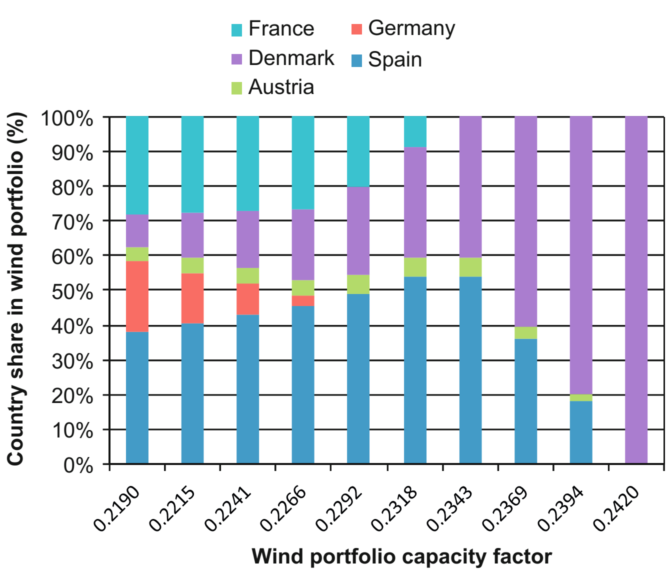

Fig. 4. Weights of unconstrained optimal portfolios—objective no. 1 ("Optimising wind power output").

to the set of optimal portfolio (the efficiency frontier), i.e. the current geographic dispersion of wind power in the five countries is suboptimal and could be modified to yield a greater wind power production for the same level of variability, or to lower the level of output variability while keeping the current level of production. Second, the evolution of the projected cross-country portfolio for 2020 goes in a good direction (greater production with less output variability), but the 2020 projected portfolios are still far from the efficient frontier. As an indication of the potential gains that could be achieved in theory, we compare the current and 2020 projected portfolios with portfolios on the efficient frontier for the same level of output variability. Potential gains in average production, for the same level of short-term variability, are about 9% for the current portfolio and range from 5% to 6% for the projected 2020 portfolios.

Fig. 4 illustrates the five countries optimal weights for portfolios along the efficiency frontier. For low variability portfolios, Spain and France have the highest weights because of their wind output low variability and good correlation properties with other countries wind output (low or negative correlations). When prioritizing average wind production, the share of installed capacity in countries with low capacity factors performance reduces to zero. In this case all power should be provided by the country with the best average/variability performance (i.e. Denmark). Comparing 2020 projected portfolios (cf. Fig. 1, Resch et al: Spain 30%, Germany 36%, Austria 2%, France 27%, Denmark 5% or Tradewind: Spain 29%, Germany 39%, Austria 3%, France 25%, Denmark 4%) with the corresponding theoretical optimal portfolio on the efficiency frontier (middle: Spain 54%, Germany 0%, Austria 6%, France 10%, Denmark 31%), we find that generally the weights of Spain, Austria and Denmark in the 2020 projected portfolios are too low comparing to the optimal theoretical portfolios, while the weights of Germany and France are too high.

3.3.2. *Objective no. 2: maximising wind power contribution to system reliability*

In this section we construct optimal theoretical portfolios in order to maximise the contribution to system reliability of wind power portfolios across the five countries, focussing on the output and variability over the peak-hours, defined as the hours with the 10% highest total demand in the year (1752 h). More precisely, we compute portfolios maximising wind energy produced during peaking-hours and minimising wind output variability during these peak-hours.

Table 6 presents some descriptive statistics derived from data from the years 2006–2007 used to compute the optimal portfolios. Denmark, France and Austria have the highest capacity factors during peak-hours, while Spain and France have the lowest production variability during peak-hours. Low and negative correlations between countries' outputs (e.g. Spain and Denmark) indicate that efficiency gains are theoretically achievable with cross-country portfolios.

Figs. 5 and 6 show the efficient frontier and weights for optimal theoretical portfolios computed using the reliability objective function. The results are similar to those described in the previous section with the other objective function. The current cross-country wind portfolio does not belong to the set of optimal portfolios and although the projected portfolios for 2020 are closer to the efficient frontier, there are still large theoretical efficiency gains possible. The portfolio average production can in theory be increased from 8% to 11% while keeping the same output variability. These theoretical gains are slightly greater than in case of the first objective function which did not concentrate only on peak-hours.

Considering the efficient frontier, for low variability portfolios, Spain and France have the highest weights because of their own low variability and good correlation properties with other countries (low or negative correlations). Surprisingly, for the reliability objective Germany is not included even in the portfolio

Table 6
Average production and correlation matrix for wind during peak hours.

	Spain	Germany	Austria	Denmark	France
Mean (peak hours)	0.250	0.245	0.278	0.293	0.259
Std. deviation	0.145	0.207	0.236	0.244	0.140
Correlation coefficients					
Spain	1.000	−0.052	0.068	−0.128	0.392
Germany		1.000	0.096	0.751	0.414
Austria			1.000	−0.074	0.042
Denmark				1.000	0.181
France					1.000

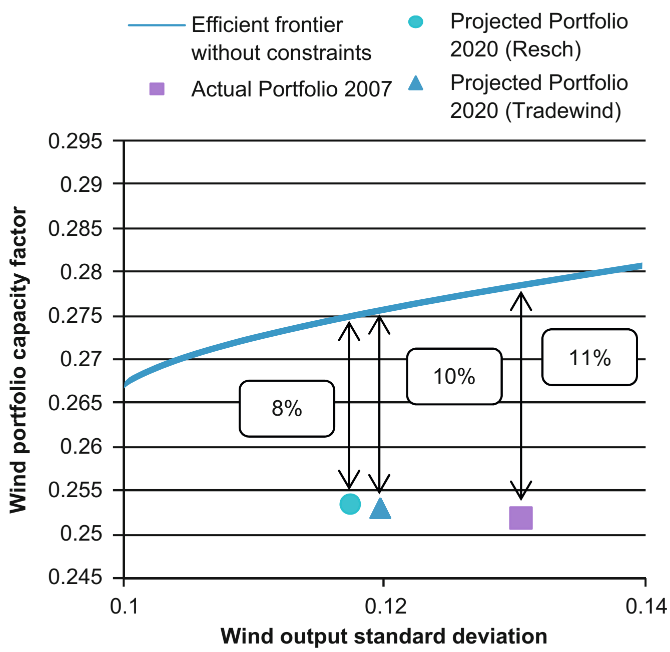

Fig. 5. Unconstrained efficient frontier—objective no. 2: maximising reliability.

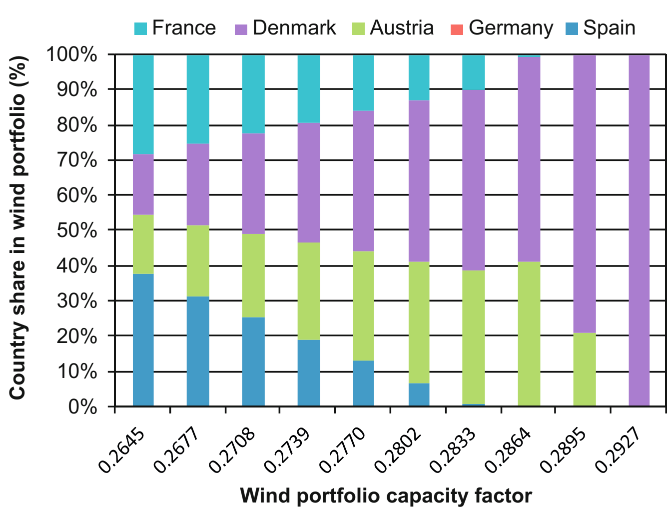

Fig. 6. Country weights in unconstrained optimal portfolios—objective no. 2: maximising reliability.

with the lowest variability. For high average production portfolios, Denmark has the highest weight given its best performances in terms of average capacity factor and variability during peak-hours. Comparing the optimal portfolios when concentrating on peak-hours to optimal portfolios obtained in the previous session which took into account all hours, the results are modified mostly for Austria and Spain. Austria has a greater weight in almost all optimal portfolios when considering the objective to maximise reliability, and this is due to the low variability of wind power in Austria during peak-hours. In contrast, Spain has a lower weight in the optimal portfolios because of the high volatility of wind power during peak-hours.

In concluding, whatever the objective function selected to build optimal unconstrained portfolios, current and projected portfolios for 2020 are far from the efficient frontier. Moreover, the geographical distribution of optimal portfolios depends on the objective considered (focus on total output or on peak-hours), as national wind power patterns do not have the same properties considering hourly variability or variability during peak-hours. Potential efficiency gains are larger for portfolios aiming to maximise wind contribution to system reliability than for portfolios focussed on total wind output.

3.4. Optimal constrained portfolios

The unconstrained theoretical optimal portfolios may not be achievable in practice because of a range of technical, political and business development constraints. In this section we develop some more realistic "constrained" portfolios by introducing constraints into the modelling when computing the optimal portfolios. We consider two types of constraints:

(i). Wind resource potential constraints. We use wind resource technical potential data for each country from Resch et al (2008).[13]
(ii). Network limitations constraints. We use a simple methodology as a proxy to represent cross-border interconnection constraints. The upper limit for wind capacity in one country is defined as the sum of a reference demand for 2020 (UCTE, 2008a) and the total transmission export capacity (projected for 2020). This gives a proxy of the maximal wind power installed capacity in each country considering that wind power energy is used for national demand and exports.

Constraints are expressed as percentages of total installed capacity for the corresponding year (for 2020 we used projected scenarios from Resch et al. (2008)). Table 7 shows the values corresponding to these two types of constraints. When constructing constrained optimal portfolio, we use first each constraint independently and then both constraints simultaneously by using the lower value of the two constraints (resource potential and network limitations) for each country.

The next subsections present successively optimal *constrained* portfolios based on the two different objectives functions: (i) Optimising wind power output, and (ii) Maximising wind power contribution to system reliability.

3.4.1. Objective no. 1: optimising wind power output

When taking into account some more realistic resource and network constraints, the efficient frontier for *constrained* optimal portfolios is below the unconstrained efficiency frontier. The optimisation program is constrained in how much it can increase the weights of the best performing countries in the portfolio. Fig. 7 represents the constrained and unconstrained efficient frontier for the objective no. 1. Despite the constraints on optimal portfolios, the projected portfolio for 2020 is still far from the constrained efficiency frontier. Potential gains from actual and projected portfolio to efficient frontier range from 4% to 7% (lower than for theoretical unconstrained portfolios for which the potential gains range from 7% to 9%). The impact of resource and network constraints on the efficient frontier is small for low variability portfolios and larger for high average production portfolios. In the one hand, the wind resource potential limits the optimal portfolio with the highest average production while the potential gains are hardly reduced. In the other hand, transmission constraints do not limit significantly the highest average production portfolio but reduce considerably the potential gains in average production for all levels of variability.

[13] See footnote no. 5.

Table 7
Portfolio constraints for 2020.

	Total	Spain	Germany	Austria	Denmark	France
Projected Wind Power capacity	93362 (Resch et al., 2008)	28,322	33,624	2074	4656	24,68
Wind Resource Potential constraints	Potential constraint (Resch et al., 2008) (MW)	50,000	58,000	3950	15,525	53,500
	Potential constraint (%)	54	62	4	17	57
Network limitation constraints	Reference demand (MW)	66,200	78,000	11,300	8508	94,000
	Export capacity (MW)[a]	2400	6480	1680	2460	5600
	Transmission constraint[b]	68,600	84,480	12,980	10,968	99,600
	Transmission constraint (%)[c]	73	90	14	12	107

[a] Information for export capacities are taken in UCTE, 2008b. For some countries where accurate information was not available for the transmission capacities for 2020 we used current export capacities increased by 20%.
[b] This line is computed as the reference demand+export capacity (MW). This represents a proxy of the maximum wind power capacity that can be installed in a country without having risk of spill-off wind energy, i.e. when wind power production exceeds local demand and transmission export capacities.
[c] This line is computed using the transmission Constraints line in MW expressed in terms of total wind power installed capacity.

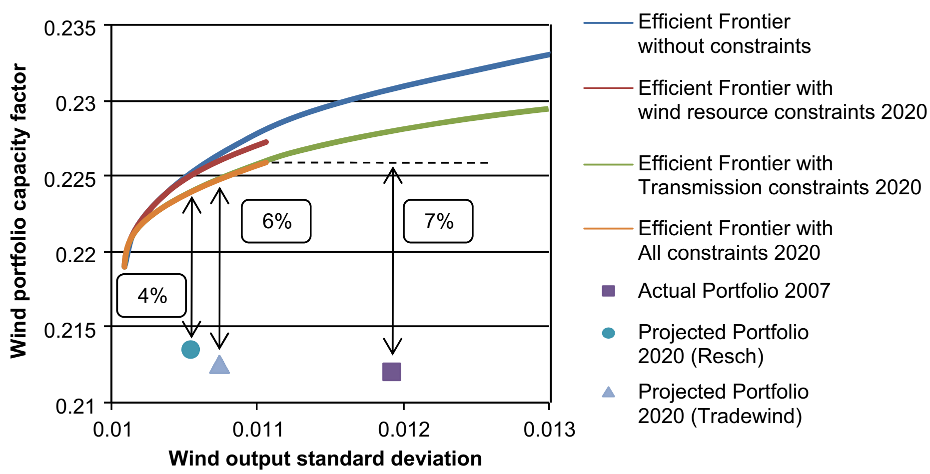

Fig. 7. Constrained and unconstrained efficient frontiers—objective no. 1 ("Optimising wind power output").

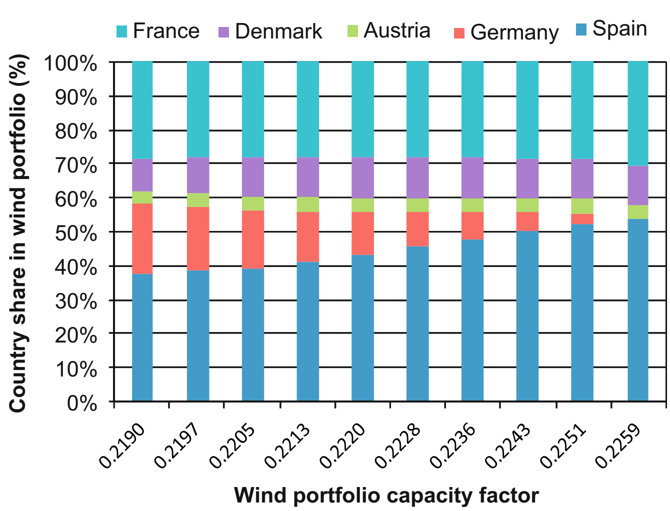

Fig. 8. Country weights in constrained optimal portfolios—objective no. 1 ("Optimising wind power output").

Fig. 8 shows the weights of the constrained optimal portfolios for the objective of minimising output variability (taking into account both resource and network constraints). For low variability portfolios, Spain and France have the highest weights in the optimal cross-country portfolios. The Denmark weight is most impacted by the transmission constraints. In the one hand, Denmark presents good performance in terms of average production and variability. In the other hand, given the limited cross-border transmission capacity (compared to national demand), wind power installed capacity in Denmark cannot be higher than 12% of total installed capacity for 2020. This limits the participation of Denmark mostly in portfolios with high average production. Austria's weight in optimal portfolios is the most impacted by the resource potential constraints (with a weight in optimal portfolios down to 4% of the total installed capacity). The portfolio with the highest performance in terms of average production has a high weight for Spain, as Spain is the country with the best properties in terms of average production and variability.

3.4.2. Objective no. 2: maximising wind power contribution to system reliability

Fig. 9 represents the constrained and unconstrained efficiency frontiers for the second objective to maximise wind power contribution to system reliability during peak-hours. Even if the constrained efficient frontier is considerably lowered compared to the theoretical unconstrained portfolios, the projected portfolio for 2020 is still far from the constrained efficiency frontier. Moreover, the impact of resource and network constraints on the efficient frontier when using the reliability objective function seems to be much more important than for the first objective which did not limit to peak-hours. Potential gains are reduced to only about 3–4% (as compared to 8% to 11% respectively for the unconstrained efficient frontier), suggesting that the transmission

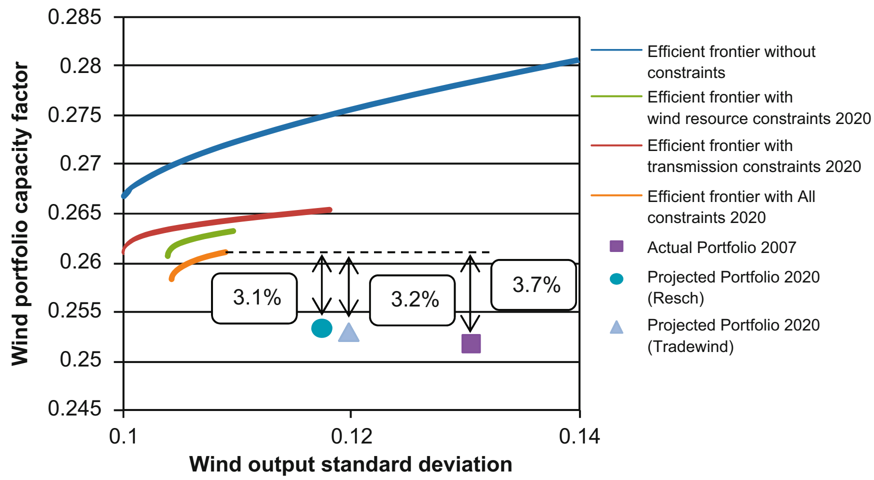

Fig. 9. Constrained and unconstrained efficient frontiers—objective no. 2: maximising reliability.

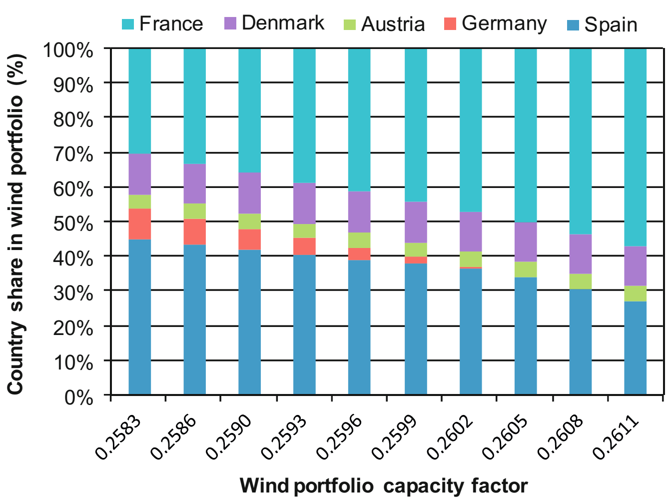

Fig. 10. Country weights in constrained optimal portfolios—objective no. 2: maximising reliability.

capacity and resource availability constraints explain a large part of the sub-optimality of projected portfolios for 2020.

Fig. 10 shows the weights of the constrained (taking into account both resource and transmission constraints) optimal portfolios for the objective of maximising wind contribution to system reliability over peak-hours. For low variability portfolios, Spain and France have the greatest weights in the cross-country optimal portfolios. Denmark and Austria weights in the optimal portfolios are the most impacted by the constraints. Denmark and Austria present good performance in terms of average production and variability during peaking-hours, but the limited transmission capacity (compared to national demand) and the limited wind resource potential limit wind power installed capacity in Denmark and Austria to 12% and 4% respectively of total installed capacity for 2020. These constraints therefore limit the weight of Denmark and Austria in all portfolios. When considering the objective to maximise wind power contribution to system reliability, the portfolio with the highest performance in terms of average production has a high weight for France, as France is the country with the best properties in terms of average production and variability during peaking-hours.

To sum up, when taking into account resource and transmission constraints in the construction of optimal wind power portfolios accross the five countries, the efficient frontiers for both objectives are significantly lowered, suggesting that the transmission capacity and resource availability constraints explain a large part of the sub-optimality of projected portfolios for 2020. However, there remains considerable room to improve the efficiency of the projected 2020 portfolios through a more efficient geographic location of wind farms, either to increase average output or to reduce output variability. Moreover, we find that the resource and transmission constraints do not impact in the same way all the countries, and that depending whether the focus is on output optimisation or on the maximisaiton of wind power contribution to system reliability, the optimal geographical distribution of wind portfolio varies to a great extent.

4. Conclusion and policy implications

There is a large discrepancy in the wind resource across European countries, and the correlation between wind output decreases with the distance between two wind farms, such that there should be some benefits in coordinated deployment policies across European countries to encourage investment in geographic locations with good wind output properties from a system perspective. Conventional investment–planning models lack the capability to represent the intermittent nature of renewable and the impact of correlations in wind power output on total wind portfolio output and variability. Wind power intermittency has implications both for wind integration costs into the electricity system (balancing costs) and for the costs associated with maintaining an equivalent level of system reliability (back up costs).

This paper introduced a new modelling approach borrowed from the financial literature which captures the benefits of geographical diversification of wind farms to reduce output variability. We demonstrated how the Mean-Variance Portfolio theory can be used to optimise wind power portfolios across different European countries. The paper used historical hourly wind production data from five European countries (Austria, Denmark, France, Germany, and Spain) and applied the Mean-Variance Portfolio theory to identify portfolios that minimise the total variance of wind production for a given level of production. The methodology was then elaborated further to derive more realistic optimal *constrained portfolios* of wind power deployment for 2020 taking into account the constraints associated with national wind resource potential and with cross-border transmission constraints.

Although highly simplified, our modelling approach demonstrated the usefulness of the Mean-Variance Portfolio theory for wind power planning and provided a number of interesting insights relevant to the current policy debate. We found that projected portfolios for 2020 for the five countries are far from the efficiency frontier representing optimal cross-country portfolios, suggesting that there could be large benefits in a more coordinated European renewable deployment policy providing incentives for location of new wind farms so as to maximise the efficiency of the overall European wind portfolio.

These findings are relevant to the current policy debate on the burden sharing of the European Commission renewables deployment targets to 2020, and suggest that the national deployment targets should take into account the benefits arising from geographical diversification, as well local wind resource constraints. Our findings suggest that there would be large system efficiency gains in a flexible approach to national deployment targets by putting in place a mechanism for renewable credit trading across countries.

Second, our results demonstrated how optimal cross-country wind portfolios differ depending on whether the focus is on minimising overall wind power volatility or whether the focus is on maximising the contribution of wind power to system reliability during peak-hours. These two objectives can be interpreted respectively as minimising system balancing costs or maximising the contribution of wind power to system reliability. Policy makers should therefore consider which objective is more relevant for wind power development across Europe and orientate support policies in order to drive investment toward efficient geographical location of wind farms.

Moreover, our results show that transmission network and wind resource limitations can reduce considerably the potential of efficiency gains through geographic portfolio optimisation by combining different wind production patterns across countries. Relieving cross-border network constraints and improving European electricity markets integration are therefore priorities to enable an optimal geographic wind power deployment across European countries.

Finally, coordinating national renewables support schemes is critical to create a level playing field that would lead investors to integrate the portfolio effects associated with locational aspects in the deployment of wind power. This in turn would require renewable support schemes that make a link between revenue and electricity market price in order to give incentives to portfolio improvements (e.g. green certificates, premium, etc.), provided that electricity market design incorporates locational pricing (Hiroux and Saguan, 2009 this issue). More ambitious policies could also consider introducing some locational incentives in the European coordinated support schemes, such as for example a feed-in-tariff (or premium) with a locational component that would integrate geographic portfolio optimisation benefits, or a European green certificates trading scheme which would integrate these geographic portfolio effects.

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