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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 5 European countries (Austria, Denmark, France, Germany, and Spain) and applies Mean-Variance Portfolio theory to identify cross-country portfolios that minimize 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 output variability at the country level dominate optimal portfolios. 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. Such constraints limit the theoretical potential efficiency gains from portfolio diversification effects, but there is still considerable room to improve performance from actual or projected portfolios. These results highlight the need for greater coordination of EU policies in support for renewables deployment, for more interconnection capacity, and for harmonization of market design and grid connection rules. Moreover, a mechanism for renewables credits trading could help aligning wind power portfolios with the theoretically efficient geographic dispersion.

Keywords: wind power variability, geographic diversification, optimal portfolios, mean variance portfolio theory

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 20% cut of carbon emissions cut by 2020 and an increase of the share of Renewables in primary energy use to 20% by 2020. The power sector is expected to provide much of the increase, such that this translates into a target of 30-40% of renewables in the electricity generation mix by 2020 (EWEA, 2008). 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 accounts for about 4 % of the total electricity demand in 2007 (EWEA, 2008). 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 & Perez, 2007), Faundez, 2008), (Fouquet & 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 equivalent 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)]. While such integrated investment planning models require an extremely detailed representation of the electricity system, 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 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 portfolios across different countries. Mean-Variance Portfolio (MVP) theory has been used in the financial sector to identify portfolios of bonds or assets which minimise 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 5 European countries (Austria, Denmark, France, Germany, and Spain) and applies Mean-Variance Portfolio theory to identify portfolios that minimise the total variance of wind production 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, transmission constraints, and policy implementation barriers.

The rest of the paper is organised as follows. The next session gives some background on the current wind power capacity in Europe, the wind power potential, and the patterns of wind power production across the different countries considered. The third section applies Mean-Variance Portfolio theory to identify optimal wind power portfolios based on these patterns of wind power production, using historical wind production data from Austria, Denmark, France, Germany, and Spain for 2006 and 2007. The paper concludes by highlighting some policy recommendations emerging from the analysis, particularly how a mechanism for renewables credits trading could help aligning wind power portfolios with the theoretically efficient geographic dispersion.

2 WIND POWER DEVELOPMENT IN EUROPE

2.1 The current wind power capacity in the EU and the support mechanisms

At the end of 2007, the total installed wind power capacity worldwide exceeded 93 GW and more than half (56.5 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.

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	2,489	2,889	3,116	3,118	3,128	3,136	3,125
FRANCE	93	148	257	390	757	1567	2,454
GERMANY	8,754	11,994	14,609	16,629	18,415	20,622	22,247
SPAIN	3,337	4,825	6,203	8,264	10,028	11,623	15,145

Source : EWEA, 2008

Table 1 shows that installed capacity in these 5 countries has been growing consistently over the past years, despite a slow down in Austria and Denmark in recent years. In 2007, wind power generation represented about 3.3% of electricity demand in Austria and more than 21% of electricity demand in Denmark, but investment in wind capacity has nearly stopped since 2002 because of regulatory uncertainty (Agnolucci, 2007). France has seen over the past two years very fast growth of wind energy (installed capacity increased by 57% between 2006 and 2007), but wind power only represents about 1.3% of the French electricity demand. More than 20 GW of wind turbines had been installed in Germany and 15 GW in Spain at the end of 2007, covering respectively 7% and 12% of the German and Spanish electricity demand.

The differences of wind energy development across European countries can be explained by a variety of economical, technical, and regulatory factors. First, the European countries have different wind energy potentials – i.e. different wind resources.[1] However, the countries with a good wind energy resource are not necessarily those with greatest wind power capacity development (e.g. France).Regulatory issues and support schemes are critical in explaining the differences in the wind power development rates across countries. The European Directive 2001/77/CE provided a general framework for supporting renewable energies.[2] But the subsidiary principle explains the wide range of different economic instruments used by member state to support the development of wind energy (European Commission, 2005, 2006). Table 2 summarizes the promotion policies that have been implemented in selected countries.[3] In its assessment of the efficiency of the different support schemes, the European Commission concluded that feed-in tariffs bring better certainty for investors concerning their profit on midterm, but that the level of the fixed tariff is crucial for enabling a real takeoff of the technology (European Commission, 2005). 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.

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 load factor

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

[2] This directive set several objectives at the national level such as the European renewable energy share in the final energy consumption (European Commission, 2001). But because of the subsidiary principle, it is up to each member state to determine its renewable support scheme insofar as it respects state aid European policy.

[3] The different types of Renewable support schemes can be defined as follows:

- **Feed-in tariffs**: A fixed price is guaranteed for a long-term period for all the electricity fed into the grid. This reduces considerably investment risks.
- The **environmental premium** scheme: Under this scheme a fixed premium on the top of the market price is paid to wind energy. This environmental premium has been applied in Spain, and shows good results in terms of wind energy development (Del Rio Gonzalez, 2008).
- The **tendering procedure**: a series of tenders for the supply of renewable electricity is managed by the government. The winner is paid at the price resulting from the tendering procedure. The additional costs associated with the purchase of renewable electricity are passed on to the end-consumer of electricity through a specific levy.
- **Green certificates:** On the one hand, wind power producers sell electricity on electricity markets. On the other hand the wind power producers sell on a specific market the green certificates that electricity suppliers are obliged to buy unless they fulfill the obligation through internal renewable production.

Austria	Feed-in tariffs for 12 years at fixed priced (7,6 c€/kWh) with two years at a reduced price

Moreover, the European Commission pointed out the lack of harmonization and coordination for the support mechanisms of renewable energy (European Commission, 2006). The European Commission fears that the diversity of support mechanisms and the lack of coordination and cooperation between member states could lead to an ineffective development of wind farms. 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 latest proposal for the European directive on the promotion of renewable energy encourages a coordinated approach at the European level in order to collectively reach the 20 % target of renewable energy in the final energy demand in 2020.

2.2 Wind power development scenarios and the EU 2020 objectives

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, 2008), (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 3 different scenarios for the development of wind power in Europe.[4] Resch et al. (2008) model the development of wind energy using the Green-Net computer model.[5] Table 3 compares the projected development of wind energy capacity (MW) for the five selected countries in these different scenarios.

Table 3. Scenarios of wind power capacity for 2020 (Source: Resch, 2008 and TradeWind 2007)

Scenario	**Tradewind**			**Resch et al 2008**
Countries	**Low**	**Medium**	**High**	**Realisable scenario for 2020**
Austria	1700	3500	4900	2 074
Denmark	4778	5309	5840	4 656
France	23000	30000	37000	24 686
Germany	34170	48202	56640	33 624
Spain	29653	35170	40186	28 322

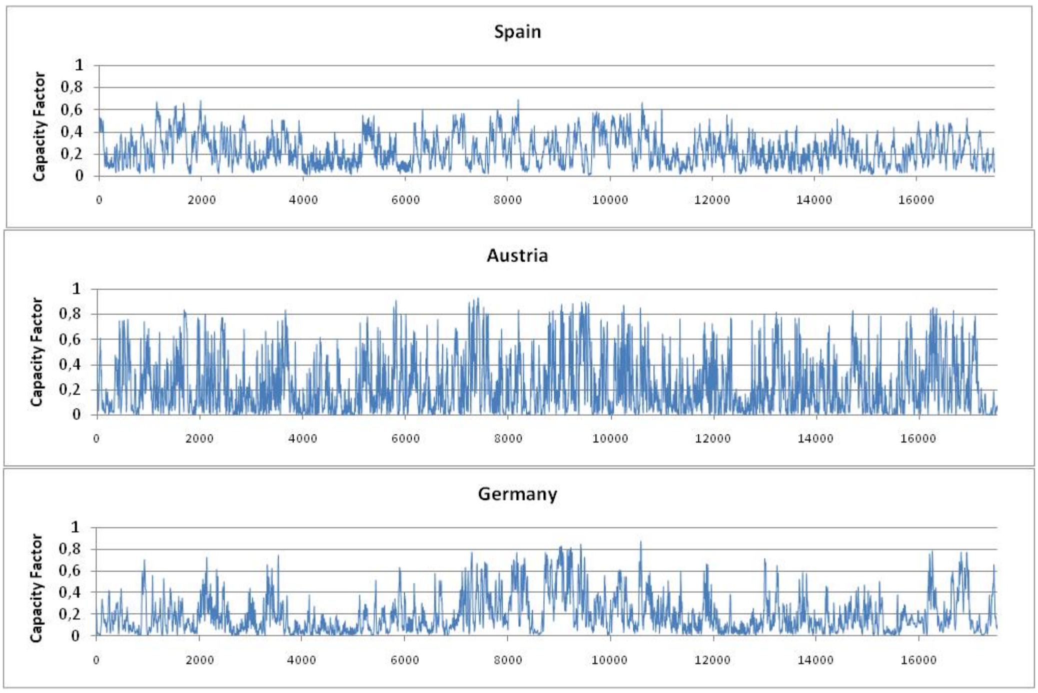
[4] The MEDIUM scenario corresponds to the most likely to outcome in the future whereas the LOW and HIGH scenarios correspond respectively to the lowest and the highest “credible” outcomes (Tradewind, 2007).
[5] These scenarios rely on three different definitions of wind power potentials: i) the theoretical 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 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 scenario which is lower than those from Trade Wind.

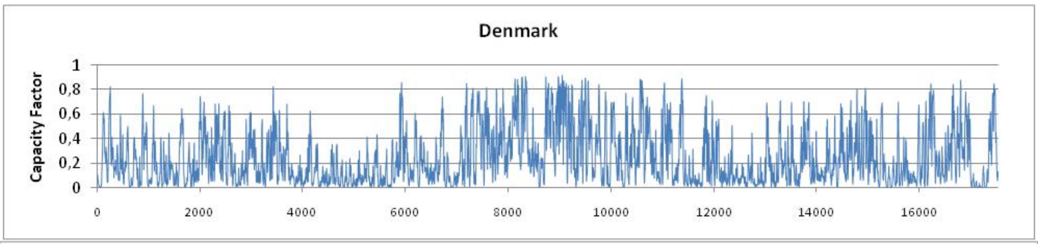
From a methodological point of view, these scenarios use a "bottom-up" approach by evaluating the potential in each country and aggregating the results at the European level, based on wind resources and technical and policy considerations. In this paper we use a different modelling approach using the different countries' wind resource patterns (in terms of output and volatility) as the core feature to assess the 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).

2.3 Optimising the wind resource use and limiting variability across the EU

At the European cross-country level, wind power production follows markedly different patterns in the different countries that are illustrated in the Figure 1, based on two years of wind power hourly production data 2006-2007). The hourly capacity factor of wind power production seem to be much less volatile in larger countries such as Spain, France, and to a lesser extent Germany than in Austria and Denmark.. Table 5 shows some descriptive statistics about the mean value of capacity factors and its hourly variability based on two years of historical data (2006-2007) for the 5 selected European countries. Denmark has the highest capacity factor mean value while Germany the lowest, but the biggest countries such as Spain, Germany and France present the lowest variability.

Figure 1 – European countries' wind patterns (hourly capacity factor from 2006 to 2007)





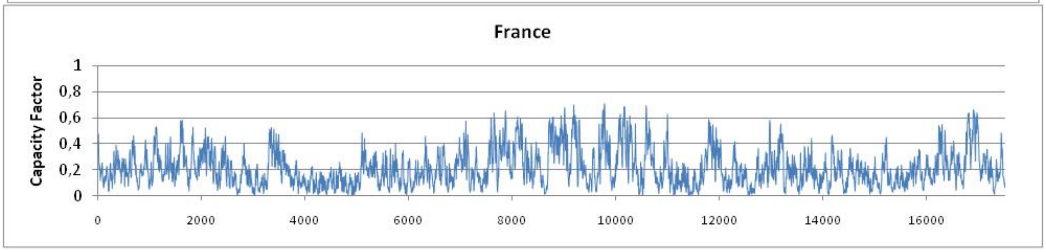


Table 5: Descriptive Statistics of wind power – Capacity factors[6]

	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

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. The variability of wind power can be smoothed out by geographic dispersion. Any type of variability can be reduced by combining weakely correlated wind productions. 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, 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 different wind patterns could lead to a global portfolio of wind power production that can be more or less variable and that can have more or less average production. The optimisation of wind energy 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.

[6] This table is built using hourly data for wind power production (published in the TSO' websites) and wind power installed capacity from EWEA 2008. Data is further described in the next section.

- The minimisation of the output variability can be smoothed out by a greater 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.[7] Reliability costs are associated to the contribution of wind power to the peak situations and to the corresponding variability of wind power generation during these periods (Milligan 2002, Giebel 2005, Gross et al 2006, Holtinnen et al 2007). When intermittent wind generation replaces conventional generation, an additional installed generation capacity is needed to get the same level of reliability (e.g. a given value Loss of Load Probability).[8]

3 APPLYING MEAN-VARIANCE PORTFOLIO THEORY TO IDENTIFY OPTIMAL WIND POWER PORTFOLIOS

This section applies Mean-Variance Portfolio (MVP) theory to identify optimal wind power portfolios across Austria, Denmark, France, Germany, and Spain. We first explain Mean-Variance Portfolio (MVP) theory in the context of energy planning and then explain the different issues when applying MVP to optimise wind power portfolios. We then demonstrate the use of 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 5 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.[9] 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.

[7] High short term variability increases system costs due to modification in the unit commitment, reserves, and needed balancing actions (Gross et al 2006, Holtinnen et al 2007).
[8] A related topic mentioned in the literature is the so-called "capacity credits". Capacity credits are a measure of contribution of wind power installed capacity to the system reliability (i.e. adequacy). As capacity credits for wind power are 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).
[9] See e.g. Elton and Gruber (1994) and Fabozzi et al. (2002) for a recent review of the developments of Portfolio theory.

Portfolio risks and returns are calculated as follows (Elton and Grubber, 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:

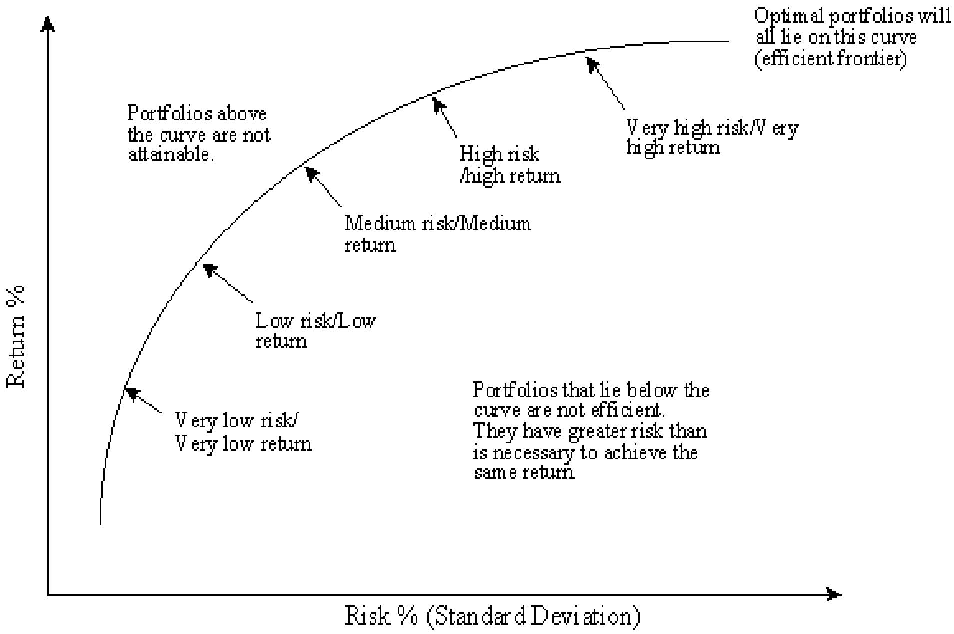
$$E(r_P) = \sum_{i=1}^{N} X_i E(r_i)$$

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

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

where ρij represents the correlation between the returns r_i and r_j of the two assets.

Figure 2 - Efficient frontier for a portfolio of 2 risky assets



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 classes included. These are known as optimal portfolios, which lie on the efficient frontier. Figure 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, 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).[10] Based on projected unit costs and volatility covariation patterns, such studies determine "efficient" (Pareto optimal) portfolios of generating assets. As Awerbuch and Berger (2003, page 5) observe, *"the important implication of portfolio-based analysis is that the relative value of generating assets must be determined not by evaluating alternative assets, but by evaluating alternative asset portfolios. Energy planning therefore needs to focus less on finding the single lowest cost alternative and more on developing efficient (i.e. optimal) generating portfolios"*.

Bar-Lev and Katz (1976) pioneered the application of MVP theory to fossil fuel procurement in the U.S. 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 U.S. 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 through 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 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 deployment planning, Mean Variance Portfolio (MVP) theory appears as a well suited tool to optimise the trade off between maximing wind portfolio output and minimising 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 UK. They construct optimal portfolios that maximise wind power generation and minimise total variance.

[10] Most studies define portfolio return as the reciprocal of unit generating cost (reciprocal of cost per kWh) and price risk in terms of price volatility per holding period (per year) but Jansen et al. (2006) argue that such approach has several pitfalls and that for transparency, it is better to use directly a simple cost frontier rather than a return frontier.

Milligan and Artig (1998), Hansen (2005), and Datta and Hansen (2005) applied portfolio theory to find "geographic" portfolios in different region of US. Portfolios are built in order to maximise "reliability" i.e. maximising wind power production and minimising variance during these peak hours. Combination of sites with negative correlated production is the main reason of improvement of constructed portfolios.

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 <u>at all times</u>; and ii)*"Maximising wind power contribution to system reliability"* which consists in maximising wind power production and minimising variability <u>during peaking-hours</u>.

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

i) ***Optimising wind power output.*** In this case we build 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. It is important to note that we do not use "anachronic" variance of the wind production computed from data time series directly (as in Drake and Hubacek 2007) but the variance of the hourly variation of wind production ($P_t - P_{t-1}$). This allows taking into account the temporal hourly variation of wind power and not anachronic variations (Boccard 2008).

ii) ***Maximising wind power contribution to system reliability.*** We build portfolios considering peak situations variability or reliability cost problem. Here 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 maximization of portfolio capacity credits.[11]

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.[12] Hourly data is verified to be indexed with the same time reference system. For each country data is normalized using installed capacity for computing hourly capacity factors.[13] This allows us to work independently of installed

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[11] 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).

[12] Wind production data was collected from the Transmission System Operators or Distribution System Operators. Most part of the information is available in the corresponding websites.

[13] 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 2008). Cf. Table n° 1.

capacities. Hourly demand data by country for the years 2006 and 2007 is collected and used to select peaking-hours and be able to separate wind power production during these hours.

In the following sections optimal portfolios of wind power installed capacity for today and 2020 are computed and compared with actual portfolio in official EU scenarios. As the wind power in different countries have different patterns, combining the installed capacity in a given way can result in different efficiencies in terms of variability and average capacity factors. One important assumption here is that countries are free to develop their own portfolio of wind plants and that production patterns develop homogenously to current levels.[14] 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 ignores a number of important regulatory and market frameworks issues, such as grid access conditions, balancing market design, or support mechanism. Careful analysis of these frameworks is required before translating model outcomes into policy recommendations.

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). Optimal portfolios are constructed successively following the two different objectives discussed 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 variation).

3.3.1 Objective n° 1: Optimising wind power output

Table 6 presents some descriptive statistics of the data used to compute optimal portfolios, based on two years (2006 and 2007) of hourly data. Denmark, Spain and Austria have the highest average capacity factors, while Spain and France have the lowest hour to hour variability.

Table 6: Wind power capacity factor data for objective n° 1

	Spain	Germany	Austria	Denmark	France
Mean	0.229	0.195	0.229	0.242	0.214
Standard deviation (hour to	0.016	0.019	0.048	0.027	0.017

[14] 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.

hour, $P_t - P_{t-1}$)						
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

Table 6 also reports the correlation coefficients between the hour to hour 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 neighboring 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 different countries wind power output indicate that there exists a potential to reduce wind power portfolios hourly variability (or increasing the average production for the same level of variability) by spreading wind power capacities over several European countries.

Figure 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 rate of average power generation (portfolio return). Once a whole range of average power figures has been optimised, an efficiency frontier is constructed. The efficiency frontier illustrates those combinations of portfolio output and output standard deviation that are possible by varying the weights allocated to each countries' wind capacity in the portfolio. Any point located along this frontier represents a combination of wind capacity weights across countries that minimises wind output standard deviation for any given level of average portfolio power output.

Figure 3 : Unconstrained efficient frontier – objective n° 1

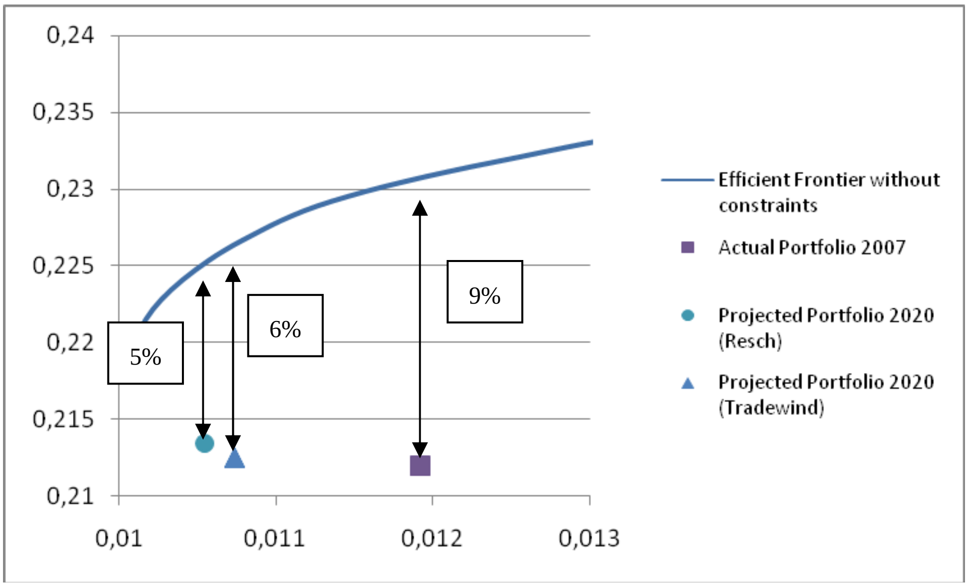
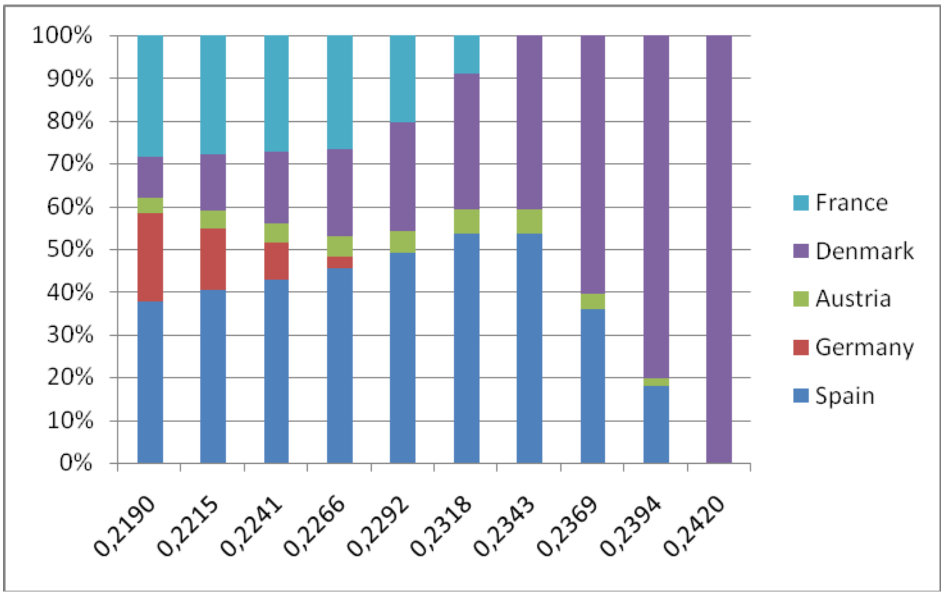


Figure 3 provides a number of interesting insights. First, the current wind power portfolio in the 5 countries considered does not belong to the set of optimal portfolio (the efficiency frontier), i.e. the current geographic dispersion of wind power in the 5 countries is suboptimal and could be modified 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 portfolios for 2020 goes in a good direction (more production and less variability) but 2020 projected portfolios are still far from the efficient frontier. As an indication of the potential gains that can be achieved with more efficient portfolios we compare actual and projected portfolio with points in the efficient frontier for the same level of variability. Potential gains in average production, for the same level of short-term variability, range from 5% to 9%.

Figure 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 own low variability and good correlation properties with other countries (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 countries with the best average/variability performance (i.e. Denmark). Comparing 2020 projected portfolios (cf. Figure 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 one specific optimal portfolio (middle: Spain 54%, Germany 0%, Austria 6%, France 10%, Denmark 31%), we find that generally the weights of Spain, Austria and Denmark in projected portfolios are too low comparing to the optimal portfolios, while the weights of Germany and France are too high.

Figure 4 : Weights of unconstrained optimal portfolios – objective n°1



3.3.2 Objective n° 2: Maximising wind power contribution to system reliability

In this section we construct portfolios 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 hours). More precisely, we compute portfolios maximising wind energy produced during peaking hours and minimising wind output variability during these peak hours.

Table 7 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 (e.g. Spain and Denmark) indicate potential gains in a portfolio combination.

Table 7 Average production and correlation matrix for wind during peaking hours

		Spain	Germany	Austria	Denmark	France
Mean (peak hours)		0.250	0.245	0.278	0.293	0.259
Std		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

Figures 5 and 6 show the efficient frontier and weights for optimal theoretical portfolios computed using the reliability objective function. The current portfolio does not belong to the set of optimal portfolio. The projected portfolios for 2020 move closer to the efficient frontier, but there is still room to improve the efficiency of these 2020 portfolios. Potential gains, measured from the efficient frontier to actual and projected portfolios, range from 8% to 11%, and are greater than in the case of the first objective 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). Surprinsingly, for the reliability objective Germany is not included even in the portfolio with the lowest variability. For high average production portfolios, Denmark has the highest proportion 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 very good qualities 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.

Figure 5 : Unconstrained efficient frontier – objective n° 2: maximising reliability

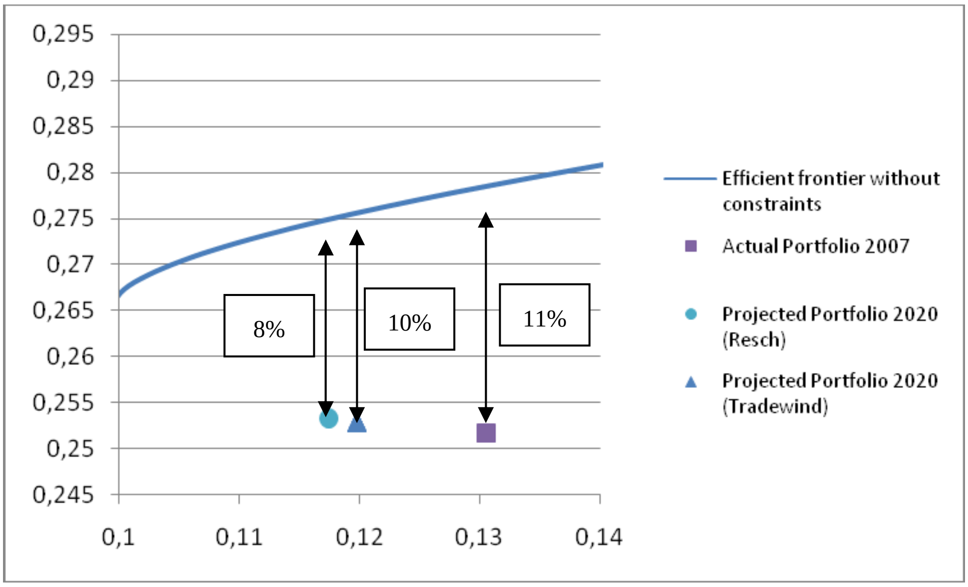
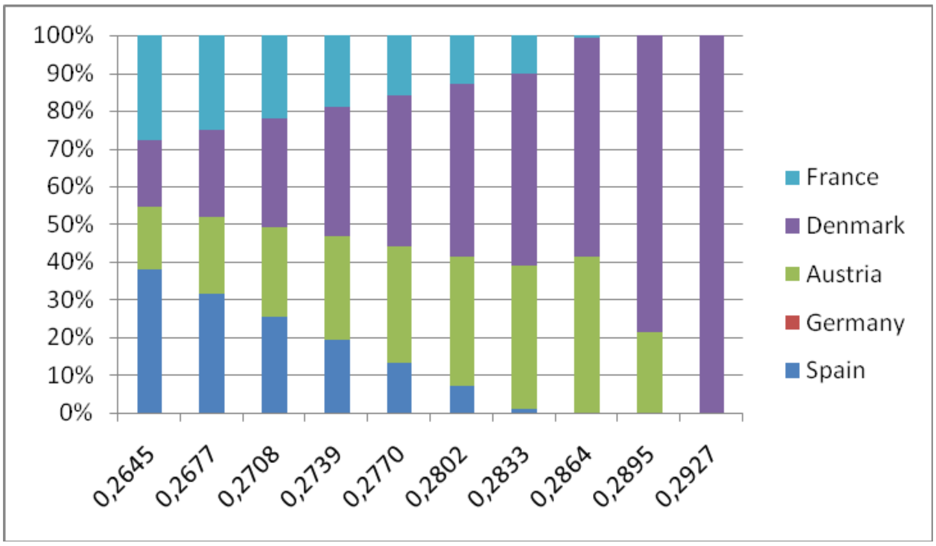


Figure 6 : Weights of unconstrained optimal portfolios – objective n° 2: maximising reliability



In concluding, whatever the objective selected to build optimal unconstrained portfolios, current and projected portfolios for 2020 are far from 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 have not the same properties considering short-term variability or variability during peak-hours. Potential 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 and the 2020 projected portfolios

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

i) Wind resource potential constraints. We use here technical potential data for each country from Resch et al (2008).[15]

ii) Network limitations constraints. We use here a simple methodology, whereby maximal network limitations constraints are given by the sum of a reference demand for 2020 (UCTE 2008a) and the total transmission export capacity (projected for 2020). This gives an indication 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) (which seems to us the most likely in terms

[15] See footnote n° 4.

of total installed capacity). Table 8 shows the values of these two types of constraints. When constructing constrained optimal portfolio, we use first each constraint independely and then both constraints by taking the lower value of the two constraints (ressource potential and network limitations) for each country.

Table 8: Portfolio constraints for 2020

	Total	Spain	Germany	Austria	Denmark	France
Projected Wind Power capacity	93362 (Resch et al.)	28322	33624	2074	4656	24686
Wind Resource Potential constraints	Potential constraint (Resch et al 2008) [MW]	50000	58000	3950	15525	53500
	Potential constraint [%]	54%	62%	4%	17%	57%
Network limitation constraints	Reference Demand [MW]	66200	78000	11300	8508	94000
	Export Capacity [MW][16]	2400	6480	1680	2460	5600
	Transmission Constraint[17]	68600	84480	12980	10968	99600
	Transmission Constraint [%][18]	73%	90%	14%	12%	107%

The results based on the two different objectives functions are successively presented: i) Optimising wind power output, and ii) Maximising wind power contribution to system reliability.

3.4.1 Objective n° 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. In fact the optimisation program is constrained in how much it can increase the weights of the best performing countries in the portfolio. Figure 7 represents the constrained and unconstrained efficient frontier for the objective n° 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

[16] Information for export capacities are taken in UCTE2008b. For some countries where accurate information was not available for the transmission capacities for 2020 we use current export capacities increased in 20%.

[17] This line is computed as the Reference Demand + Export Capacity [MW]. This represents roughly 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 exceds local demand and transmission export capacities.

[18] This line is computed using the transmission Constraints line in MW expressed in terms of total wind power installed capacity.

efficient frontier is small for low variability portfolios and larger for high average production portfolios. In the one hand, wind resource potential limit the optimal portfolio with the highest average production while the potential gains for realisable portfolio is 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.

Figure 7 : Constrained and unconstrained efficient frontiers – objective n° 1

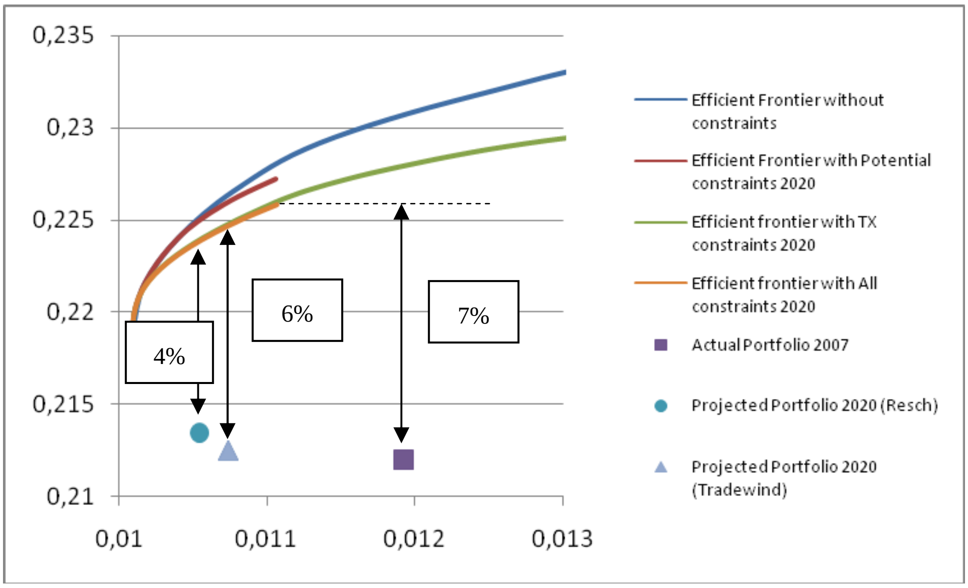
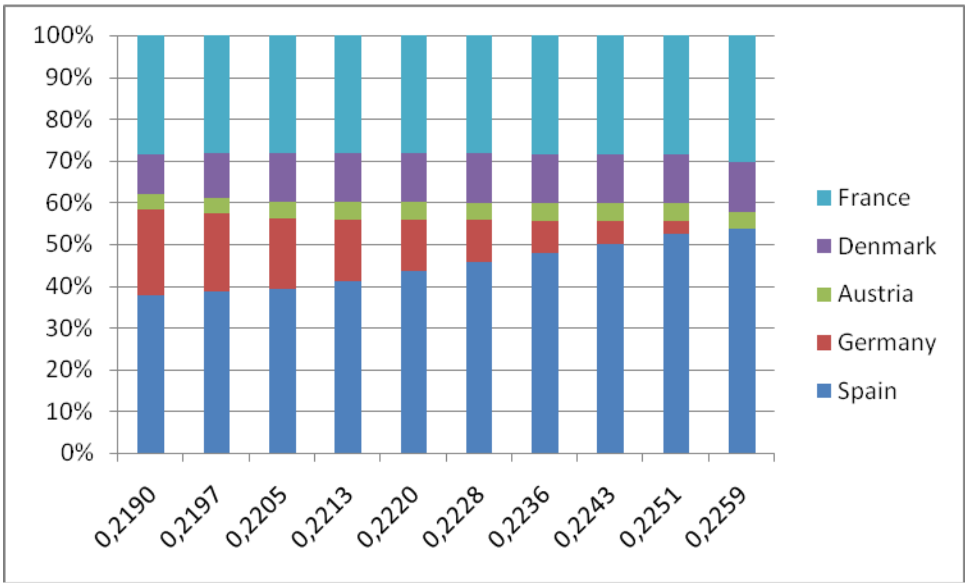


Figure 8 shows the weights of the constrained optimal portfolios for the objective of minimising balancing variability (both resource and network constraints). For low variability portfolios, Spain and France have the highest weights in the optimal cross-country portfolios. The Denmark weight is the 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 local 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 weigh 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.

Figure 8 : Weights of constrained optimal portfolios – objective n°1



3.4.2 Objective n° 2: Maximising wind power contribution to system reliability

Figure 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% to 4% (as compared to 8% to 11% respectively for the unconstrained efficient frontier), suggesting that the transmission capacity and resource availability constraints explain a large part of the sub optimality of projected portfolios for 2020.

Figure 9 : Constrained and Unconstrained efficient frontiers – obj. 2: reliability

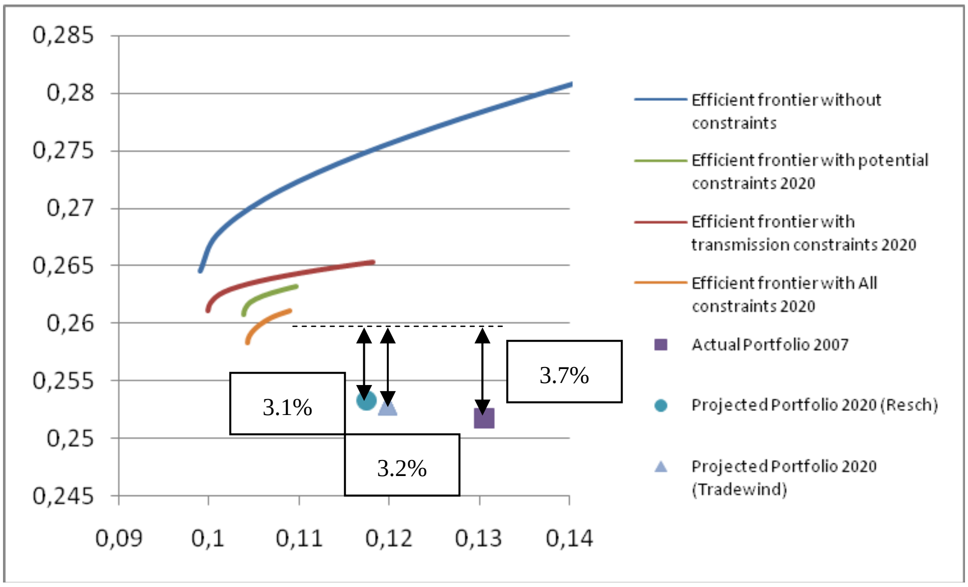
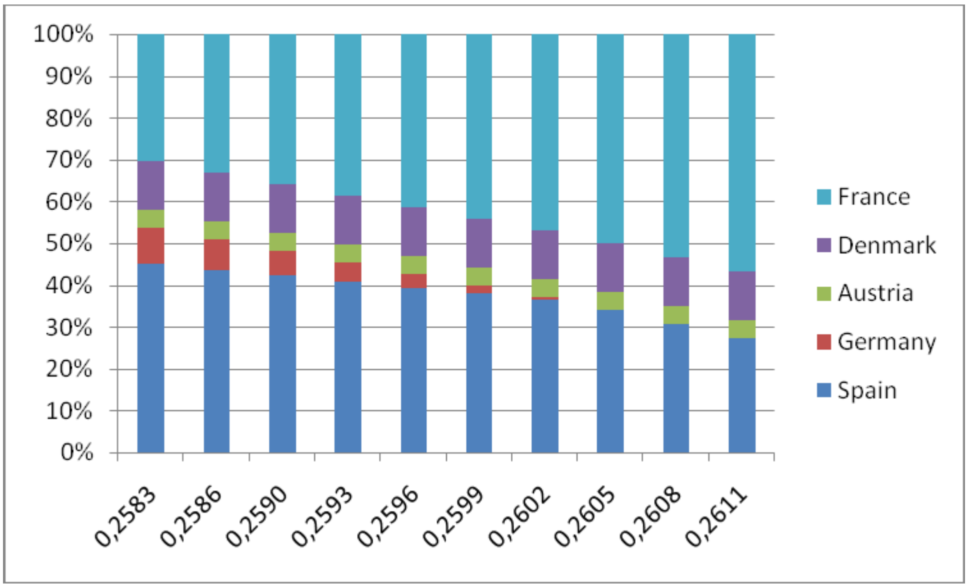


Figure 10 shows the weights of the constrained (both resource and transmission constraints) optimal portfolios for the objective of maximising wind contribution to system reliability over peak hours. For low variability portfolios, Spain and France have the greatest weights in the cross-country optimal 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 local demand) and the limited wind resource potential limits wind power installed capacity in Denmark and Austria to 12% and 4% respectively of total installed capacity for 2020. These constraints therefore limit the participation 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.

Figure 10 : Weights of constrained optimal portfolios – obj. 2: reliability



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 throug 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 Mean-Variance Portfolio theory can be used to optimise wind power portfolios across different European countries. The paper used historical wind production data from five European countries (Austria, Denmark, France, Germany, and Spain) and applied 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 under a range of constraints including national wind resource potential and transmission constraints.

Though highly simplified, our modelling exercise demonstrated the usefulness of 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 portfolios, suggesting that there could be large benefits in a more coordinated European 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 also show 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. More specifically, our modelling exercise suggests that a number of policies are key to optimize wind power geographic deployment across European countries, including: i) coordination of national support schemes for renewables; ii) improving the support scheme designs and market designs; iii) removing potential barriers to cross border flows (e.g. transmission interconnection); and iv) pursuing the European electricity market integration. Our modelling results indeed show that transmission network and wind resource limitations can reduce considerably the potential of efficiency gains through geographic portfolio optimisation gains by combining different wind production patterns across countries. Relieving cross border network constraints and better European market integration are priorities to enable an optimal geographic wind power deployment across European countries. We also demonstrated how optimal geographic wind power 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.

Finally, coordinating and harmonising national support schemes for renewables 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. Support schemes that make a link between revenue and electricity prices give incentives to portfolio improvements (e.g. green certificates, premium, etc.), provided that electricity market design incorporate locational pricing (Usaola et al 2008). More ambitious policies could also consider introducing some locational incentives in the EU coordinated support schemes, such as for example a feed-in-tariff (or premium) with a locational component that would integrate the portfolio effects or an EU green certificates scheme which would integrate geographic portfolio effects.

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