HOW LARGE SHOULD A PORTFOLIO OF WIND FARMS BE?

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Abstract

We model the financial performance of portfolios of wind farms located around Great Britain in the early 2020s. We measure the expected annual profits and their variance as the measures of performance most relevant to investors (acknowledging that system operators need to respond to short-term variations in output). The efficient frontiers contain relatively few stations (no more than four out of a possible fifteen), and the average portfolio has an efficiency of just 0.725. The correlation between the efficiency of a portfolio measured with respect to annual output and with respect to annual profits is just 0.103. Careful market analysis is needed if investors are to build optimal portfolios of wind stations.

1. Introduction

A portfolio of energy sources is likely to give better results, in terms of the trade-off between cost or profit and its variability, than relying on a single source (Awerbuch, 2000; Roques et al, 2006). Dispersing wind farms over a wide area can also reduce the impact of variations in wind speed and hence the intermittency of output (Sinden, 2007; Roques et al, 2010). Hour-to-hour variations in wind output are critical for system operation, but are unlikely to have a significant impact on profitability when measured over financially relevant timescales, such as a year. However, there can be significant year-to-year variations in wind conditions, which would have an impact on profitability, and these may differ between regions. There is also a systematic tendency for wind farms to receive prices below the time- or demand-weighted average electricity price, because the hours in which they generate are the hours in which their output depresses the price. In this context, a wind farm sited away from the bulk of a country's capacity, which therefore has different operational patterns, may receive a better average price. These are benefits from siting some stations away from the main area of wind generation, but they could be negated if this implies choosing a site with a lower average wind speed.

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This paper estimates the mean and variance of annual profits for portfolios of wind stations located around Great Britain, using a model calibrated to the 2020s. We do not study the operational problems caused by intermittency, but take into account the trade-offs between price and output discussed above. We are therefore seeking a set of portfolios that are optimal for the investor, rather than from the perspective of a system planner (who would want to take account of the externalities caused by intermittency).

We take 18 years of hourly wind speed and electricity demand data, covering the period from 1994 to 2011. The annual weather-corrected demands are scaled to a common level, which means that our hourly observations preserve any correlations between the weather and electricity demand. The wind speed data, for around 120 sites around Great Britain, are used to predict the output from turbines in each area, and national totals produced by summing these, weighted according to predictions of the distribution of turbines around the country (and its seas). We do not attempt to calculate an investment equilibrium for either wind turbines or conventional plants, although the number of Combined Cycle Gas Turbine plants is such that they make approximately normal profits (implying that neither entry nor exit should be desirable).

In every hour, we set the price equal to marginal cost as calculated with a merit-order stack, assuming that the stations with the cheapest full-load running costs are always able to meet the pattern of demand. This price is received by all the wind stations in our sample. We calculate annual profits per kW of capacity at each location, before taking the average annual profit per kW for portfolios of plants spread evenly across up to 11 sites. Eighteen years of data for each portfolio allowed us to calculate the mean and standard deviation of these annual profits.

The highest annual profits are received by a “portfolio” of a single plant, in the region with the highest average wind speed, but this also had the highest standard deviation of annual profits. Generators can reduce the variance of their annual profits by investing in a small portfolio of plant. The lowest variance came from a portfolio of just two stations, widely spaced (near the Thames and in the North-East of England); however, the owner of this portfolio would have found it unprofitable, on average, given our assumptions. The other portfolios on the frontier giving the best trade-offs between risk and return were also surprisingly small – never more than four stations.

We calculate the efficiency of every possible portfolio, based on the distance between that portfolio and the (unattainable) optimum point that combines the highest average profits and lowest variance. The efficiency measure is equal to the ratio of the distance from that point to the frontier, relative to its distance to the portfolio. This is analogous to the measurement of productive efficiency, although that is based on measurements from the origin. We find that the efficiency of a portfolio is positively correlated with its size, but very weakly so. Furthermore, the average efficiency is just 0.725.

A developer may not want (or be able) to build a full market model in order to predict the profit advantages of a diversified portfolio of wind farms. How far can these be predicted from looking at the mean and variance of annual outputs – data that are much easier to obtain? We found a correlation of 0.103 between a portfolio’s efficiency with respect to profits and with respect to output (measured in the same way). Seven portfolios were on the efficient frontier with respect to revenues, and eleven with respect to output, but only one was efficient on both measures. Three of the portfolios that were efficient with respect to output had a score of less than 0.7 with respect to profits.

The next section of the paper describes the background to this study, and some relevant previous work. Section 3 sets out our model, while section 4 describes the data we have used for demand, wind generation and the costs of conventional plant. Results are given in section 5.

2. Background

The UK is one of a number of European countries that is expected to install large amounts of wind generation over the next decade, or has already done so. The problems that the intermittency of wind generation can cause, and the need for back-up plant, are well-known, as are the potential benefits from evening out this intermittency by dispersing the stations over a large area, reducing the impact of any one weather pattern. Sinden (2007) models the potential output from wind farms dispersed around Great Britain and shows that this can significantly reduce the variability of output, although Oswald et al (2008) point out that some of the coldest winter weather coincides with high-pressure systems that produce very little wind across large areas of North-West Europe.

The impact of wind output on power prices has also become well-known. The so-called "merit order effect" (Sensfuß et al, 2008) means that prices are lower when wind output is high. Twomey and Neuhoff (2010) point out that this means that wind stations will tend to receive less than the time-weighted price for their output (except to the extent that average wind speeds are positively correlated with average prices). Green and Vasilakos (2010) simulated this effect when they used predictions for wind output in a market model to simulate the price distributions that might be expected if Great Britain built 30 GW of wind stations by 2020, showing that it could have a noticeable impact on wind generators' revenues, particularly if conventional generators were able to exploit market power.

The other branch of research that we draw on is that of portfolio theory, grouping assets together to achieve the desired trade-off between risk and return. Markowitz (1952) showed that the combination of two assets with returns that were not perfectly correlated could achieve a lower variance than either asset in isolation, and this insight has been applied in many other fields. Awerbuch (2000) was the first to apply it to energy economics, showing that adding renewables to a portfolio of conventional power stations with uncertain fuel prices could allow a given level of risk to be achieved for a lower expected generation cost, even if the renewable sources were more expensive on average than the fossil-fuelled stations. Several other applications are contained in Bazilian and Roques (2008). Roques et al (2006) make the distinction between costs and profits, pointing out that the latter can be affected by the correlation between fuel and electricity prices. For renewable stations, where this correlation is low, the socially beneficial reduction in the variance of generation costs may lead to an increase in the variation of generators' profits that the latter would seek to avoid. Delarue et al (2011) show that it is important to consider the expected operating pattern of each kind of plant when building a portfolio (and that this will depend on the capacity mix chosen), for the optimal portfolios constructed while taking this into account can differ significantly from those built around assumed load factors.

Doherty et al (2006) model the role of wind in a future Irish power system and find that it can help to reduce both the average level of generating costs and their volatility. Their stations are dispersed around the system to reduce intermittency, but the paper does not suggest that this was done via a formal optimisation process. In contrast, Roques et al (2010) apply portfolio theory to consider the optimal siting of wind farms across five European countries, treating the average load factor as the equivalent of the return to a portfolio, and the hour-to-hour change in output as its volatility. They constructed optimal portfolios for the year as a whole, and for peak hours. Rombauts et al (2011) consider the impact of transmission constraints on the efficient frontiers that can be created from seven sites across three countries, illustrating their approach with a relatively short sample of wind data from the Netherlands. The absence of transmission constraints allows each country to choose a somewhat less even distribution of wind power across its sites than would be optimal if there was no cross-border transmission capacity.

3. The Model

To calculate the annual revenues for each wind generator, we use a model in which thermal power stations are dispatched to meet the demand for electricity, net of the output of the wind stations. This demand is price-sensitive, with an assumed constant slope of minus 20 MW per £/MWh. This gives an elasticity of around minus 0.1 for high levels of demand, rising as demand falls.

Our model is built around a merit order stack in which the cheapest available stations are assumed always to be physically capable of meeting demand; in other words, we ignore dynamic constraints. In each hour, the price of electricity is set equal to its marginal cost, normally equal to the fuel and variable operating costs of the most expensive station needed. When one group of power stations is running at full (available) capacity, however, the price rises to the level at which demand is equal to that capacity. In some cases, the price will then be high enough for the next group of stations to start running at their own marginal cost.

When the net demand is particularly low, generally because wind output is high at times of relatively low gross demand, it may fall below the minimum stable generation of nuclear power stations. We assume this to be 60% of their available capacity, based on the performance of new Pressurised Water Reactors. If this were to happen, it would be necessary to constrain off some wind stations. These stations would lose output-based subsidies, and would therefore require a payment equal to the subsidy before they are willing to spill output. We assume that the market price is therefore equal to minus £50 per MWh at those times.

We differentiate between winter and summer in terms of the availability of conventional power stations and the price of gas. In winter, when some gas has to be taken out of storage, its price is 6% above the base level, whereas in summer, the price is 6% below – this is the average differential observed in the UK in the 2000s. There is little planned maintenance in the winter, and so we assume that 90% of the capacity of all types of thermal power station is available, while in the summer, availability falls to 80% as scheduled maintenance takes place. We do not adjust the output of wind stations for maintenance, implicitly assuming that this happens during low-wind periods.

We consider a brown-field scenario for conventional power stations, choosing the capacity of each type based on the expected retirements over the coming eight years and a sensible level of new investment. This keeps the energy rents that gas-fired stations earn from selling at prices above their marginal cost approximately equal to their fixed costs. This brings the system close, but not exactly, to the market equilibrium level of capacity, given our cost assumptions. We do not include any demand for operating reserve capacity, and so require less capacity than would be needed in practice – this does not affect the revenues received by wind plants, which will rarely be able to offer these services.

4. Data

Our model relies on four sets of data: the costs and available capacities of thermal generation, and hourly time-series of national demand and regional load-factors for wind turbines.

We consider nine types of thermal generation, which are listed in Table 1 in order of merit. New coal and oil generators are represented in the model, but we assume that environmental policy in Britain would prevent them from being built. Nuclear capacity is 40% below current levels as the majority of existing capacity will have been decommissioned, and only one new site (Hinkley C) is likely to have been brought online by 2020. We assume that apart from wind, of which there will be 30 GW, most new capacity is CCGT.

Plant costs were derived from five major studies: Mott MacDonald (2010), Parsons Brinckerhoff (2011) and Arup (2011) specific to the UK; plus IEA (2010) and EIA (2010) internationally. We aggregated their projections to 2020 or thereabouts for annualised investment cost (defined as the annual rent required to cover overnight capital cost plus interest over the lifetime of the plant), fixed and variable operating costs, and thermal efficiencies. Fuel costs are based on DECC's central scenario for 2020, which equated to £7.70 for coal, £33.70 for oil, and £26.53 for gas (per MWh). Carbon emissions are priced at £30 per tonne of CO_2, which is the floor price established for 2020 under the government's carbon price support scheme (HM Treasury, 2011).

The last two columns of Table 1 summarise this cost data: marginal cost consists of fuel, carbon and variable operation and maintenance (O&M); fixed cost consists of the annualised capital cost and fixed O&M. The capital cost for older vintages of coal and CCGT was assumed to be zero as they are already sunk. The interconnectors (3 GW) were assumed to import at times of high prices (in Great Britain) and were placed in the merit order to reflect this.

Table 1: Parameters for power stations in our model

	Capacity (GW)	Thermal Efficiency (%)	Variable O&M Costs (£/MWh)	Marginal Cost (£/MWh)	Fixed Cost (£/kW-year)
Wind (onshore)	11.0	–	0.00	0.00	207.90
Wind (offshore)	19.0	–	0.00	0.00	370.89
Nuclear	6.0	35%	1.00	5.00	463.84
Coal (new)	0.0	45%	2.13	42.02	235.63
Coal (old)	11.5	35%	2.13	53.25	33.41
CCGT (new)	15.8	58%	1.39	60.03	99.22
CCGT (2000s)	8.0	52%	1.39	66.82	17.70
CCGT (1990s)	7.0	48%	1.39	72.28	17.70
Oil	0.0	35%	2.00	120.49	30.00
OCGT	1.0	25%	1.84	167.73	76.93

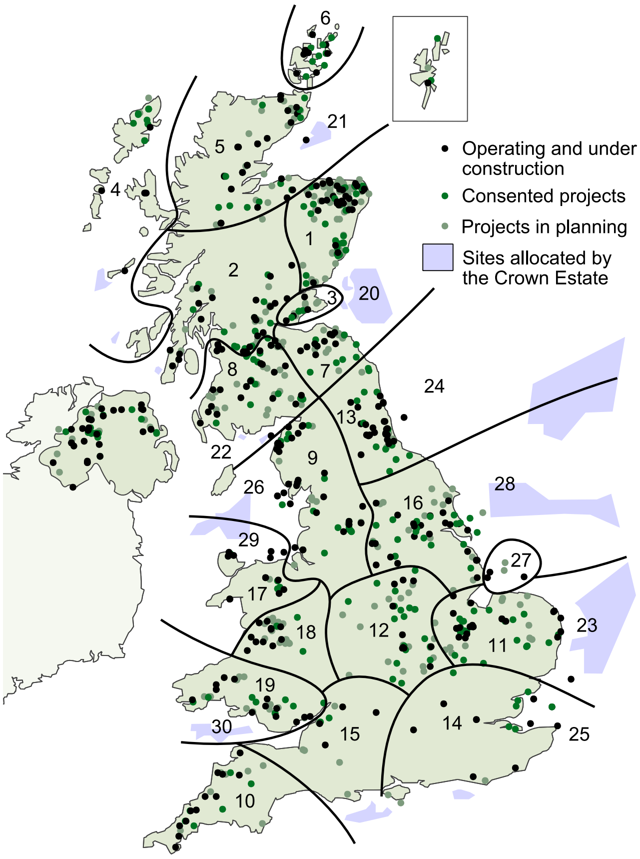
Our hourly time-series of demand data was produced from half-hourly figures published by the National Grid for the period 1994–2011. We upscale this historic demand to hypothetical 2020 levels, assuming that demand will grow by 0.7% annually to give a total of 350 TWh per year. This total includes approximately 10% of gross demand which will be met by distribution-connected wind and other on-site generators. National Grid's figures are based on transmission-connected generation and the demand which it has to meet, and therefore exclude this smaller-scale wind generation and the demand which it is meeting. We include both. The linear scale factors that we use do not reflect changing patterns in the underlying demand due to de-industrialisation and the potential electrification of heating and transport demands, so the system peak and minimum demands therefore also scale linearly (64.6 and 22.7 GW respectively).

The time-series output of wind generators was estimated using the methodology presented in Green and Vasilakos (2010) and Sturt and Strbac (2012). We obtained hourly observations of wind speed from the UK Meteorological Service (2006), collected from 120 weather stations between 1994 and 2011. Around 3% of the observations were missing or corrupt, and were filled using interpolation, regression and Markov-chain simulation. These stations were grouped into the 30 regions used in this study (19 onshore and 11 offshore) as depicted in Figure 1.

Fleets of wind farms composed of 16 leading turbine models were stochastically allocated to each region, and the power curves from these turbines were mapped onto wind speeds to give the expected energy yield and load factor for each region. Wind speeds were adjusted to account for the fact that wind farms and weather stations have different hub heights, and reduced by 10% for onshore regions to give a mean load factor of 26% – matching the historic output of UK turbines. Offshore wind speeds were provisionally inferred from coastal locations, as none of the MIDAS stations were deployed at sea, and so were increased by 10% to give an average load factor of 36%. We expect that new speed measurements from Round 3 offshore sites (shaded areas in Figure 1) will soon be made available, and will incorporate them into our data set.

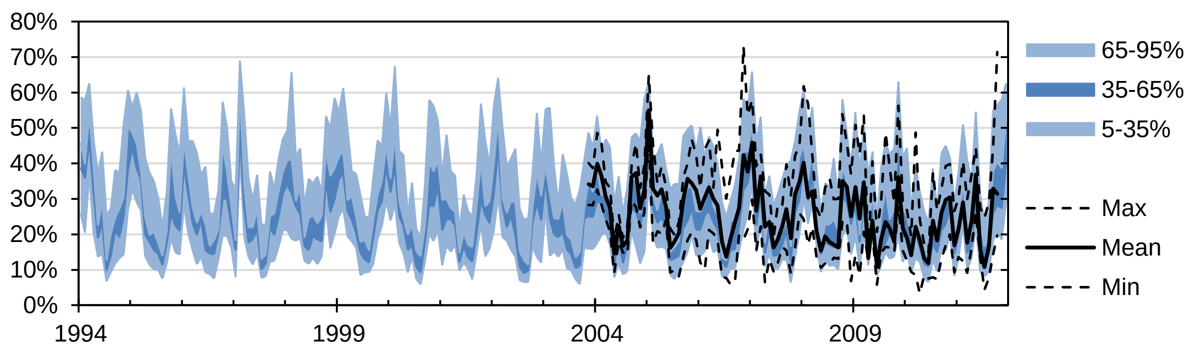
As in Sturt and Strbac (2012), we found our estimated wind outputs had an exaggerated diurnal component in comparison to historic measured output. This is due to the formation of thermal gradients in the atmosphere, which increase wind speeds at low (weather station) altitudes relative to higher (turbine hub) ones, particularly during summer months. Our estimated load factor during summer was on average 65% higher between 10:00 and 18:00 than between 22:00 and 06:00, compared to a 26% increase observed in the metered output of UK turbines. Left uncorrected, this would overestimate the value and profits of wind generators, as electricity prices are generally higher during the day than overnight. A set of seasonal corrective factors were applied to align the estimated and observed diurnal patterns.

Figure 1: Map of Great Britain divided into the thirty regions used in this study, depicting the location of current and planned wind generators.



The final data set contained hourly load factors for the thirty regions, which closely resemble the pattern and distribution of actual output from transmission connected turbines in the UK. Figure 2 compares the spread in our estimated load factors with historical output derived from Elexon data and Renewables Obligation Certificate (ROC) submissions.

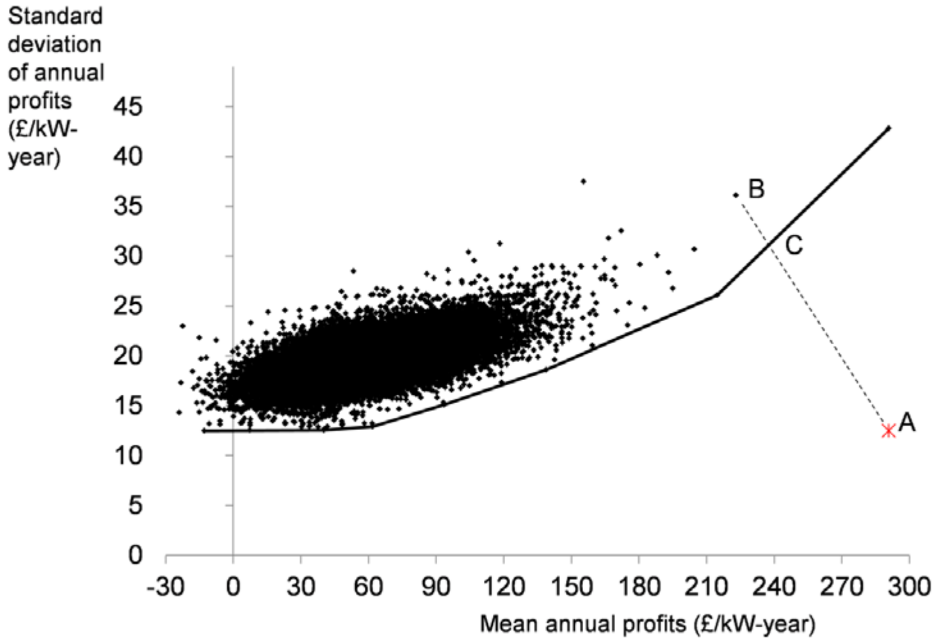
Figure 2: Monthly average load factor across the thirty regions, comparing simulation (shaded areas) with measured historical output (lines).



5. Results

The profit for each wind farm is equal to the value of its output at market prices, plus revenue from the Renewables Obligation Certificates (valued at £50 per MWh of output, whenever that output is produced), less the assumed annual cost of £207.90 per kW reported in Table 1 above. Given our assumptions, our model predicted an average annual super-normal profit of £38/kW-year for wind stations, with an average standard deviation (measured across the years for each station individually) of £22/kW-year. A few stations made losses in some years; some made losses in every year. We will refine the allocation of wind capacity within regions to ensure that we are not building stations at sites expected to be unprofitable, although it is worth noting that some profitable investments may have been made in the past when the cost of wind turbines was not driven up by supply chain constraints.

Figure 3: Mean and standard deviation of annual profits.



We used 19 onshore regions in our model, but limit our portfolios to no more than 15 of these – this requires us to consider 32,767 portfolios, and each additional region doubles the number. The four regions that we excluded from the portfolios had expected annual profits that were negative, and were very highly correlated (0.93 or above) with those of another region. This made them unlikely to bring any diversity benefits to offset their unattractiveness as a stand-alone investment.

Figure 3 shows the mean and standard deviation of the annual profits for each of our portfolios. The best portfolios are those towards the bottom right of the Figure, showing high expected profits with little variability. The star (labelled “A”) shows the combination of the highest observed profits and the lowest standard deviation from any of our portfolios – since these came from two different portfolios, this point is not attainable in practice. Seven points form the efficient frontier, where it is impossible to increase the expected profits of a portfolio without increasing their standard deviation.

Most of the portfolios lie above the left-hand half of the efficient frontier, with only a small number offering expected profits of more than £150/kW-year. The portfolios on the frontier are given below in Table 2:

Table 2: Optimal portfolios of onshore wind farms

Mean Profit (£/kW-year)	Standard deviation (£/kW-year)	Region(s) included:			
291	43	Fife			
215	26	Fife	Hebrides		
139	19		Hebrides		
93	15	Devon	Hebrides		
62	13	Devon	Hebrides	North East	
40	13	Aberdeen	Hebrides	North East	Thames
-13	12			North East	Thames

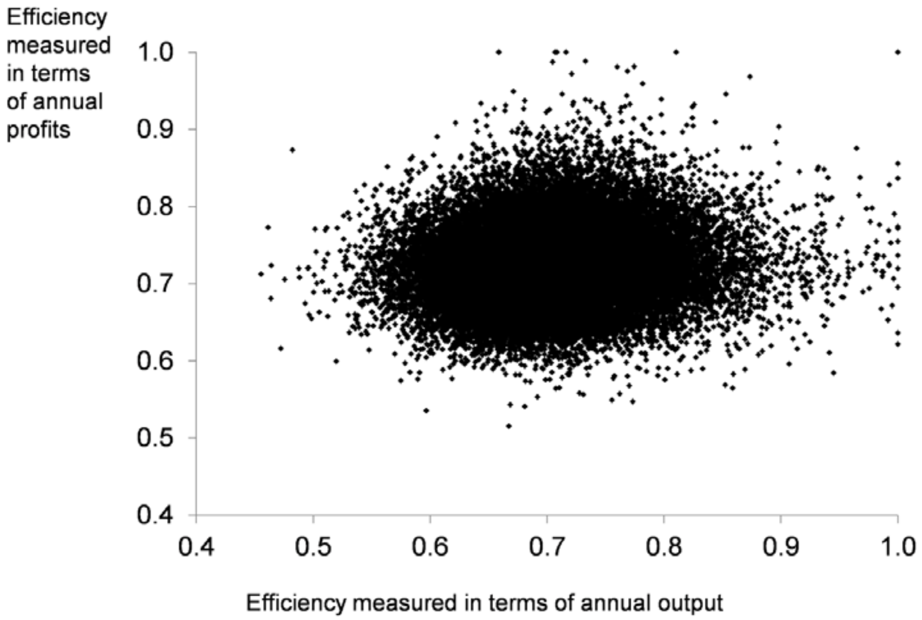
The most profitable portfolio is that of a single region, Fife in the east of Scotland, which has the highest annual outputs in our data. The Hebrides, the islands to the north-west of Scotland, also have high outputs. The portfolios with less risk include stations from distant parts of Great Britain – the Thames Estuary in south-east England, Devon (and Cornwall) in the south-west and the North East of England (or Aberdeen in north-east Scotland). Surprisingly, the portfolio with the lowest risk contains just two stations – its expected profits are negative, however, making it an unattractive investment.

We will define the efficiency of a portfolio in terms of its closeness to the efficient frontier. We take our underlying concept from the measurement of productive efficiency, which uses the ratio of the input: output relationship actually achieved by the unit being assessed to the best relationship observed in the data among similar units. In productivity studies, efficiency is often measured in terms of an input-output ratio, and relative to the origin. In this context, we will measure relative to the point given by the asterisk: the (unachievable) combination of the highest expected profits and lowest risk, labelled as point A. For any other point, such as B, its efficiency is assessed along the ray from point A to the point being assessed, and relative to the point where this ray intersects with the efficient frontier (or rather its convex hull), point C. The efficiency score is then the ratio of AC to AB. It is equal to 1 for a point on the efficient frontier, and falls as the distance between the point being assessed and the frontier increases. The average efficiency score of our portfolios is 0.725 and the minimum score is 0.515.

A developer might not wish to build a full market model to assess the profitability of its proposed stations; furthermore, the exact profits that we predict are sensitive to the details of the model. Would it be sufficient to assess the prospects for a station on the basis of its expected annual output and its variance? We could draw an efficiency frontier analogous to the one in Figure 3, but using the data for each portfolio’s annual outputs. In this case, there are eleven stations on the efficient frontier, an average efficiency score of 0.707, and a minimum score of 0.455.

The average efficiency scores are similar, but only one portfolio is efficient when measured both against output and against profits. The efficient portfolios based on output are somewhat larger than those based on profits: three contain four stations, three contain five, and one portfolio consists of six stations – still a small proportion of the fifteen being considered. The correlation between the two efficiency scores is only 0.103. Selecting a portfolio that offers a good combination between the average level of annual output and its variability is far from a guarantee of a similar relationship for annual profits. Figure 4 shows the pattern of efficiency scores across all of our portfolios.

Figure 4: Portfolio efficiency, measured by profits and by output.



6. Conclusions

We have modelled the expected level and annual variation in the profits from portfolios of onshore wind farms distributed around Great Britain in the 2020s. For investors, this is a more relevant timescale than the hourly variation which has been the subject of previous work in this area, and is of course critical to system operators.

We find that the optimal portfolios consist of stations sited in no more than four out of the fifteen regions we study, suggesting that the benefits of diversification can be achieved quite easily on this time scale. The choice of portfolio is important, however, because the average efficiency across all the 32,767 portfolios that we assessed was just 0.725. (We measured the efficiency of each portfolio relative to the frontier and the (unattainable) point with the maximum average and minimum standard deviation found in our sample.) This means that the portfolios must be carefully chosen if they are to reduce the variation in annual profits without sacrificing too much expected profitability.

We also calculated the efficiency of every portfolio in terms of the expected level and variability of annual outputs. The mean efficiency was similar, at 0.707, and we found a very weak relationship between the two measures, with a correlation coefficient of 0.103. Developers should not rely solely on measures of output when designing an optimal portfolio of wind farms, but should consider the interaction between wind output and electricity prices. A small number of high-priced hours (typically on winter days with relatively low wind) are responsible for a significant proportion of each generator's profits, and it will be the correlations between the stations' outputs in these hours, rather than over the year as a whole, that govern the behaviour of their profits.

One aspect of these results is provisional: our data for offshore wind farms is currently based on weather stations near the coast, rather than those at sea. Weather data for offshore sites is to be released in the near future: we do not expect that the revised output figures would lead to qualitative (as opposed to quantitative) changes in our results. We shall extend the analysis to consider portfolios that combine onshore and offshore stations.

Our results could well be affected by the market design in force. We have modelled the current system of renewable energy support in Great Britain, which gives generators one revenue stream from market prices and a second from selling Renewable Obligation Certificates that depend on the level of output, but not its timing. The UK government is planning to move towards a so-called Feed-in-

Tariff with Contracts for Differences. Under a pure Feed-in-Tariff, generators' revenues are independent of the timing of their output, and portfolio analysis based on output data would translate directly to profitability. Whether that would hold for the UK government's scheme (which retains exposure to intra-year market prices for at least some generators) depends on details yet to be decided. Another dimension to electricity market design concerns the degree of geographical differentiation in prices – the impact of this on incentives for diversification is a subject for further research. Persistent price differences would make stations in low-priced regions less attractive to generators, but variation around the mean may reinforce the incentive to own a diversified portfolio.

Generators can often get a better trade-off between the expected level and the annual variability of their outputs by building a portfolio of geographically dispersed stations. The interactions between output levels and prices are such that a portfolio designed to optimise the mean and variance of output levels may well prove sub-optimal from the point of view of revenues. Careful analysis of the market would be required for generators that wish to maximise their expected revenues without excessive volatility.

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