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Sensitivity study of a wind farm maintenance decision - A performance and revenue analysis

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A B S T R A C T

Commercial operation and maintenance of wind farms always involves trying to find the most cost-effective solution from various possible options. In this paper, a maintenance action within a Spanish wind farm was studied, whereby a blade replacement was required to prevent catastrophic failure. The conducted replacement was accompanied by an underperformance resolved in a later blade re-pitching. We analyse the decision taken in terms of the power performance and net present value from the cash flow resulting from the energy sales. The impact of the timing of the maintenance is discussed in various what-if scenarios. The sensitivity to environmental causes of underperformance is compared by varying the duration of blade icing and comparing the performance in different wind directions. Country dynamics and subsidy impacts are hypothetically evaluated for the prevailing electricity market conditions as if the turbine were operating in either Spain, Netherlands or the UK. The findings highlight the uncertainty in power performance and the importance of maintenance accuracy. It is shown that the decision-making of operators should not only consider the seasonality of the wind resource, but also the seasonality in electricity markets.

1. Introduction

There has been a significant amount of research into the financial feasibility of wind farm installations. Application of various evaluation frameworks has showed e.g. that the feasibility is strongly influenced by capacity factor and electricity market price fluctuation, whereas the nominal power and inflation rate were found as only slightly influential on the payback period of an investment [1]. Further studies have discussed the importance of the wind resource, turbine selection, farm layout and country policies [2–4].

With increasing importance of operation and maintenance (O&M) costs, sensitivity studies to maintenance policies have gained more attention. Wind farm maintenance simulation and optimisation tools have been developed and results have showed that turbine availability was sensitive to the shift length of the service team and failure rates of components [5–7]. Repair time, inspection timing and inspection accuracy were found to be strongly affecting whether corrective, preventive or predictive maintenance strategies were most effective [8–11]. Kerres et al. [12] state that corrective maintenance is the most cost-effective strategy for the components of the drive train. Leigh and Dunnet [13] show that periodical replacements of subsystems significantly decrease the number of required corrective maintenance visits. A maintenance decision is also highly dependent on the environment, since environmental variables are significantly correlated with failure occurrences [14] and accessibility is also dependent on the weather [15]. Most research on optimising wind farm maintenance focused on generic strategies, however the complexity of real maintenance decisions and their financial consequences have not gained much attention.

To analyse the impact of maintenance decisions, the wind turbine performance has to be evaluated. The common way of addressing the performance, is by deriving a power curve using 0.5 m/s bins of the wind speed and calculating mean values of the power production for each bin [16]. Improving the method of bins by accounting for the non-linear power vs wind speed relationship and deriving multiple curves for different direction sectors has

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been discussed [17]. Other work compared different types of parametric power curves [18]. Further non-parametric models have been developed by applying machine learning and data mining techniques to wind turbine power curves [19–22]. Other work has also investigated multivariate models, i.e. models that do not only consider wind speed as an input, but also other parameters [23,24]. Schlechtingen et al. [23] showed the advantage of an adaptive neuro-fuzzy inference system (ANFIS) considering the ambient temperature and wind direction. However, these advanced models have not yet been compared with real data from more challenging conditions like complex terrain and stall-regulated turbines. In addition, simplistic assumptions of losses were often taken in the context of financial studies of maintenance strategies without considering measured performance at all.

If the financial impact of underperformance is to be analysed, the details of the income generation need also to be considered. Most European wind farms sell electricity to the electricity market and/or might get some form of country-specific subsidy [25–27]. The complex interactions of country policies and market dynamics have been investigated in life cycle analyses [4], but not addressed in the context of optimising O&M from the perspective of a wind farm operator.

Case studies based on real data can give an insight into the complexity and sensitivity of decisions that simulation tools cannot provide. In this paper, we address maintenance decisions based on extensive case study data while addressing how the financial consequences can be calculated most realistically.

This work discusses a sensitivity study of a maintenance decision in a Spanish onshore wind farm, namely a preventative blade repair to avoid catastrophic failure. The intervention caused a temporary underperformance of the turbine. The energy losses are quantified in a performance analysis and revenue is evaluated with a discounted cash flow. Possible alternatives to the decision taken are investigated and compared with the sensitivity to environmental effects such as icing and wind directional distribution. The impact of country characteristics such as electricity prices, subsidies and taxes is discussed and compared for three countries: Spain, UK and Netherlands. A preliminary study by the authors highlighted already differences between the impact of Spanish and UK electricity market prices in this context [28].

The remaining part of the paper is structured in six parts. Section 2 introduces the case study data, section 3 describes the approach used and section 4 shows the results of the performance analysis. The analysis of the sensitivity to the various effects is given in section 5. The two subsequent sections 6 and 7 cover the discussion about and the conclusions of the study, respectively.

2. Case study data

The study is conducted based on data from a Spanish wind farm with stall-regulated turbines with a rated power of 900 kW, which were commissioned in 2002. The turbines are located on ridges in complex terrain at altitudes of approximately 1500 m. One turbine is selected for this analysis, but the observations are representative for many turbines in the farm.

Fig. 1 illustrates the farm layout and an assessment of the terrain (according to [29]). It can be seen that the terrain slopes are mostly higher than 10% with values up to 30% for some sectors. The selected wind turbine has wake free sectors for 93° to 210° and 306° to 355°, with the latter corresponding to the predominant wind direction as shown in Fig. 2.

Available operational data consist of SCADA records and met mast measurements from mid-2012 to mid-2017. Missing information is approximated with data from a met station at approx. 35 km distance [30] and NCEP reanalysis results for the turbine location [31]. The financial studies are conducted with hourly day-ahead electricity market prices from the European Network of Transmission System Operators [32] and interest rates given by Organisation for Economic Co-operation and Development [33].

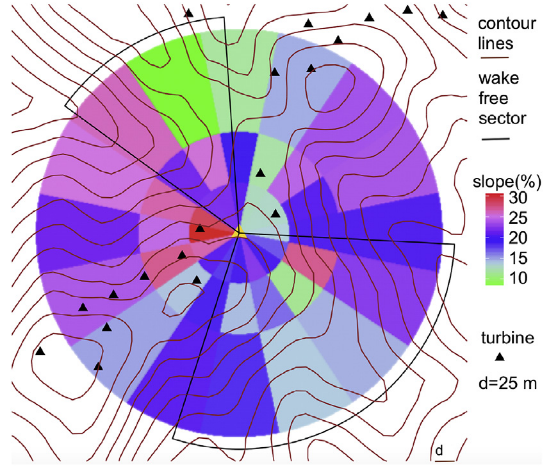

Fig. 1. Layout of wind farm. The terrain complexity is illustrated with the slopes of four planes fitted with the selected turbine (0–5, 5 to 10 and 10 to 20 times the turbine diameter, respectively).

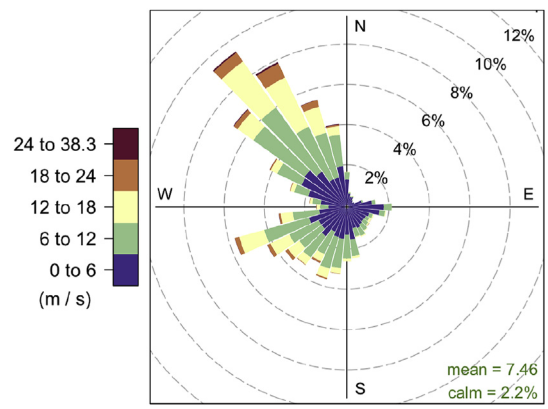

Fig. 2. Wind rose for July 2012–May 2017 with 10° sectors.

Table 1
Summary of case study data.

Category	Variable	Resolution
Turbine SCADA	Wind speed mean	10 min
	Wind speed variance	10 min
	Active power mean	10 min
	Ambient temperature mean	10 min
	Generator speed mean	10 min
	Nacelle direction mean[a]	10 min
Wind farm met mast	Pressure	10 min[b]
Met station [30]	Pressure[c]	1 day[d]
NCEP [31]	Relative humidity (at 850 mbar)	6 h
ENTSOE [32]	Day-ahead market price Spain	1 h
	Day-ahead market price UK	1 h
	Day-ahead market price Netherlands	1 h
OECD [33]	Consumer price index	1month
	Long-term interest rate	1month

[a] Approximation for unavailable wind direction.
[b] Incomplete data for 2013, 2014 and June 2016.
[c] Substitute for missing data, altitude corrected.
[d] Average of daily minimum and maximum recording.

The data variables used are summarised in Table 1.

Maintenance has been documented in service reports and unstructured comments in spreadsheets. A simplified summary of the maintenance history for mid-2012 to 2015 is given in Table 2 excluding routine services. The major interventions are the replacement of the blades in May 2015, illustrated in Fig. 3, and a re-pitching of the blades in September 2015. In the current industry practice for stall-regulated turbines, blades are replaced with a pitch angle which might be sub-optimal. In the subsequent months the performance is checked with a focus on matching the designed rated power of the generator. Then a re-pitching takes place to increase or decrease the power output. In the farm investigated, the re-pitching was required to increase the power output. Re-pitching of blades is feasible from inside the nacelle without a crane. This optimisation procedure is based on the technician's experience and involves a degree of ‘trial and error’.

3. Methodology

This study aims to analyse the detailed impact of a blade replacement. The impact is evaluated by firstly analysing the power performance with respect to the maintenance history. Subsequently, the financial consequences are assessed by establishing a cash flow for the maintenance investment and revenue from energy generation.

Finally, a what-if sensitivity study is conducted in which different maintenance timing scenarios are compared in terms of the energy generated and financial results.

3.1. Performance monitoring

Performance monitoring of wind turbines is different to monitoring other machines, as the expected power is fluctuating and a function of the unobserved wind speed in front of the turbine. To properly analyse the efficiency of the turbine, environmental effects should be first excluded. The most critical assessment of the turbine's performance is usually conducted in the period after the installation of the machine, based on additional met masts, and standard procedures [29].

In operation, wind farm owners might focus on collecting the turbine's power production, nacelle wind speed and temperature data inside the turbine as maintaining met masts and meteorological sensors over the turbine's lifetime is costly. Consequently real ambient temperature, pressure, relative humidity, precipitation and icing data might not be recorded continuously.

Guidance on performance evaluation based on nacelle measurements and influencing external effects is given in the dedicated IEC standard [16]. However, these procedures are not necessarily applied in practice and detailed guidelines for pre-processing data are lacking.

Table 2
Maintenance history of the investigated turbine.

Number	Date	Type	Event
1	09/2012	Repair	Brake pad replacement
2	05/2013	Inspection	Blade inspection
3	07/2013	Repair	Anemometer replacement
	07/2013	Inspection	Main bearing inspection
4	09/2013	Repair	Blade repair on site
5	04/2014	Repair	Tower repair
6	08/2014	Repair	Communication repair
7	10/2014	Repair	Converter repair
8	05/2015	Major repair	Preventative blade replacement
	05/2015	Repair	Repair of brake pumps
9	09/2015	Optimisation	Re-pitching of blades

Fig. 3. Photograph of a blade replacement in the wind farm investigated (copyright, CETASA).

If the wind speed is measured on the top of the nacelle, the characteristics of the flow are changed due to the interaction of the turbine itself, though some attempt is often made to adjust measurements using a nacelle transfer function during the certified power curve testing at a test site. Procedures to generate a ‘free-stream’ wind speed from nacelle measurements require an initial calibration with a met-mast [16], but this is not necessarily feasible for a farm in complex terrain.

The air density affects the generated power linearly and a correction of the power to a reference density might be appropriate. Air density is usually indirectly derived with supporting variables such as pressure, temperature and relative humidity [16]. If necessary, missing data might be complemented by nearby meteorological stations and atmospheric re-analysis databases such as NCEP [34]. Where humidity, temperature or pressure measurements are missing or incomplete, air density calculations rely, in the case of this farm, on secondary information as listed in Table 1. A mean air density of $1.0219\ \mathrm{kg/m^3}$ is calculated with a standard deviation of $0.0274\ \mathrm{kg/m^3}$ (note the altitude of approx. 1500 m). Density can be corrected with a factor using the instantaneous density and a reference or average density [16]. In our case, density correction does not result in any improvement of the power curve accuracy, but even a slight worsening (scaled mean absolute error (sMAE) increases from 4.07% to 4.11%). This might be influenced by the use of secondary information for relative humidity and pressure. Based on these findings, it was decided to omit density correction in the further part of this study.

Periods that coincide with icing of blades should be filtered in advance of any power performance analysis [16]. Since precipitation and icing data are not available in this case study, icing is assumed if relative humidity $> 80\%$ and temperature $< 2\ ^\circ\mathrm{C}$ according to current practice [35]. This filtering results in a clear improvement of the power curve (sMAE from 4.07% reduced to 3.61%) giving the best trade-off between accuracy and complete data.

The wake of neighbouring wind turbines will affect the performance, but we do not limit the study to the sectors that are unaffected by a wake in order to get a complete picture of the turbine's performance in reality. Further environmental effects on the wind turbine performance are wind turbulence and gusts, wind shear and atmospheric stability, 3-dimensionality of flow and topographic effects. These effects are rarely measured or analysed in operation, but may have a significant impact [36,37].

Sufficient data from representative operation are needed to derive a power curve representing all seasons. If different power curve modelling techniques shall be compared, a second period is required for validation of the prediction performance. Two periods of one year were identified that were at least affected by maintenance intervention: September 2013 to August 2014 (training) and October 2015 to September 2016 (validation). It should be noted that this implies that the validation takes place after the blade replacement of the turbine, but a better test case was not feasible.

A standard power curve based on the method of bins was compared with two multivariate versions of the method of bins considering seasonality and wind directions, respectively. The seasonality is addressed by deriving one power curve for each three month season. The effect of wind direction was considered by classifying in 12 wind direction sectors, i.e. 30° each, and deriving an individual power curve for each one. Further on, the ANFIS model as proposed in Ref. [23] was analysed with four configurations addressing the same multidimensional character of performance:

a) Univariate model: wind speed
b) Multivariate model: wind speed, temperature
c) Multivariate model: wind speed, nacelle direction
d) Multivariate model: wind speed, temperature, nacelle direction

The prediction accuracy of the models was evaluated with metrics scaled to the turbine rated power as proposed in Ref. [23]: mean absolute error (sMAE), mean error (sME), root mean squared error (sRMSE) and standard deviation (sSD).

3.2. Cash flow analysis

Before any fixed asset is purchased, the decision about expenditure must be evaluated by taking into account associated possible future profits [38]. The estimated profits are derived in a discounted cash flow analysis that considers the time value of money. Any investment can be compared with the risk-free alternative of keeping this money in the bank (or similar investments), which defines the minimum attractive rate of return (MARR). The selection of MARR can be done based on long term interest rates and inflation rate (consumer price indexes).

Financial assessment of engineering decisions can be clustered into various groups such as a) Equipment or process selection from various options, b) Replacement of the existing equipment [38]. The cash-flow set-up and the evaluation procedure vary for the two categories. Although the maintenance decision studied in this paper is a blade replacement, the decision does not belong to the second category above as in replacement analyses the change of equipment is optional, where the annual equivalent cost estimations are required for the remaining useful life-time of the existing asset and service life-time of the candidate asset. Here, the replacement is mandatory and only various options are possible in terms of the procedure and timing. For the evaluation of the alternative options, candidate indicators can be listed as Net Present Value (NPV), payback period, internal rate of return (IRR) and inflation adjusted rate of return (IARR).

Table 3 shows the advantages and disadvantages of the indicators with NPV emerging as the most suitable measure for this study.

$$\mathrm{NPV}(i, N) = \sum_{t=0}^{N} \frac{C_t}{(1+i)^t} \tag{1}$$

In the NPV equation, t is the time step, C stands for cash flow, i represents interest rate and N the total number of time periods. Common time steps are one year, one quarter or one month. Annual cash flow is most popular, however, it requires an annually averaged interest rate and does not consider the timing in the year. NPV decision rule states that the selection from alternatives can be made according to ranking of NPVs. NPV can be used to make a decision among mutually exclusive projects, which means selection of one causes the exclusion of others [39].

3.3. Sensitivity study setup

What-if studies are conducted to analyse the financial impact of the maintenance intervention with the main consequence of underperformance due to a sub-optimal pitch angle. This underperformance was studied by changing the delay of the optimisation and the timing in the year. Total losses due to downtime were given to examine in contrast. The financial consequences were compared with results of performance changes due to variations of environmental conditions, namely icing occurrence and wind direction. The impact of country characteristics was evaluated by comparing Spain, UK and Netherlands and with different taxes and subsidies.

The financial evaluation was set with a discounted cash flow focusing on the maintenance action, the blade replacement and the re-pitching of blades. As the real cash flow in a wind farm is very complex and case specific, a simplified chronology was used with an initial investment for the repair costs which was payed off in the subsequent years. The acquisition of the turbine was neglected and all generated income was utilised to balance the maintenance expenses. We limit the utilised energy sales to two years to consider that in reality income is not only used for the maintenance costs. The resulting cash flow was not realistic in terms of the values, but serves for a relative comparison. The repair costs were back-dated to 2014 as spare blades needed to be acquired before the actual repair could take place. Energy sales were considered starting from May 2015 as this period covers the blade replacement.

For the baseline of the sensitivity study, the energy production in the two years was taken as recorded by the SCADA system without any filtering except for invalid signals. For the study of the various effects, the performance was modified by conducting the following steps:

1. Check which condition applies in the investigated time period
2. Define power curve for reference and each applicable condition of the turbine (see section 4.2)
3. Interpolate power production according to reference power curve with wind speed measurement
4. Interpolate power production according to power curve for first applicable condition with wind speed measurement
5. Check that the turbine operates and the actual production is not already higher than in the power curve of condition (in case of power increase, or lower in case of decrease)
6. Derive difference of interpolated power production as power correction
7. Filter the correction to allow only up to 5% deviation from the new power curve (with only upper limit for power increase and only lower limit for power decrease)

Table 3
Financial indicator selection [38,39].

Indicator	Advantages	Disadvantages
IRR	independent of the accuracy of interest rate	misleading for the selection among the projects, difficult to compute
IARR	shows the effect of the inflation	dependent on IRR
Payback period	simple	low resolution, no time value of money
NPV	tracks the direct impact of the project	dependent on the accuracy of interest rate estimation, long computing time

8. Repeat steps 4–7 for all conditions and apply the power correction resulting in the lowest power production for each time step.

This procedure was taken to make sure that the original variability in performance due to further effects remained. It also ensured that the worst power curve was applied if multiple causes of underperformance happened simultaneously.

The performance modifications due to different maintenance scenarios were purely calendar-based. For the investigation of different timings of the intervention in the year, the duration of the underperformance was unchanged, i.e. the underperformance was only ‘shifted’ by a number of months. Scenarios involving additional icing were set by applying the condition to the dates with lowest temperatures. The variation of the turbine performance related to wind direction was applied only to the two selected wind direction sectors.

In the next step, income was generated by applying the power production to the electricity prices. In general, electricity markets are based on the selection of the generation with the lowest marginal costs, also known as merit order. In many cases, there are wholesale electricity markets for different temporal dimensions such as forward and future, day-ahead and intra-day markets. In this study, day-ahead market data were used.

The general seasonality of energy prices in the relevant period is shown in Fig. 4. Production values were grouped to fit the hourly time resolution of the market data. A monthly cash flow was established by summation of revenue on a monthly basis. The NPV analysis considered the real interest rate [38] with inflation and interest rates as shown in Fig. 5.

The comparison of country dynamics was implemented under the assumption that the market prices were not correlated to the wind conditions of the country. To justify this assumption, the Kendall correlation of the electricity market price with the wind energy production as given by ENTSO-E [32] is shown in Table 4. In addition, the correlation of the market price with the wind speed at the location of selected large onshore wind farms (Spain: Marachon, Netherlands: Westereems, UK: Whitelee) taken from NCEP [31] is given. It can be seen that wind speed and wind energy production are both negatively correlated with the market prices. The correlation is somehow significant in Spain, but negligible in Netherlands and UK. That means that applying Netherlands and UK electricity prices to a Spanish farm with possibly different wind speeds, should not introduce significant bias. Investigating UK country characteristics requires a conversion of the initial investment from EUR to GBP. The final NPV results are converted back to EUR for comparability. We used a fixed exchange rate of 1 EUR = 0.7871 GBP as the average from May 2014 to May 2017 for both conversions.

The taxable income can be calculated by deducting expenses from energy sales and thus depends on the operator's financial situation. For simplicity, we applied corporation tax to 10%, 20%, 30% of the sales revenue. The tax rate varies in the countries being 25% to 28% for Spain, 25% in Netherlands and 20%–21% for UK depending on the year [40].

The impact of subsidy schemes was also investigated. Although there has been recently some attempt to harmonise and liberalise state aid in the EU [41], there are still various subsidy frameworks for wind energy in force such as fixed feed-in tariffs, premiums, green certificates and tax exemption rules. Fig. 6 illustrates the

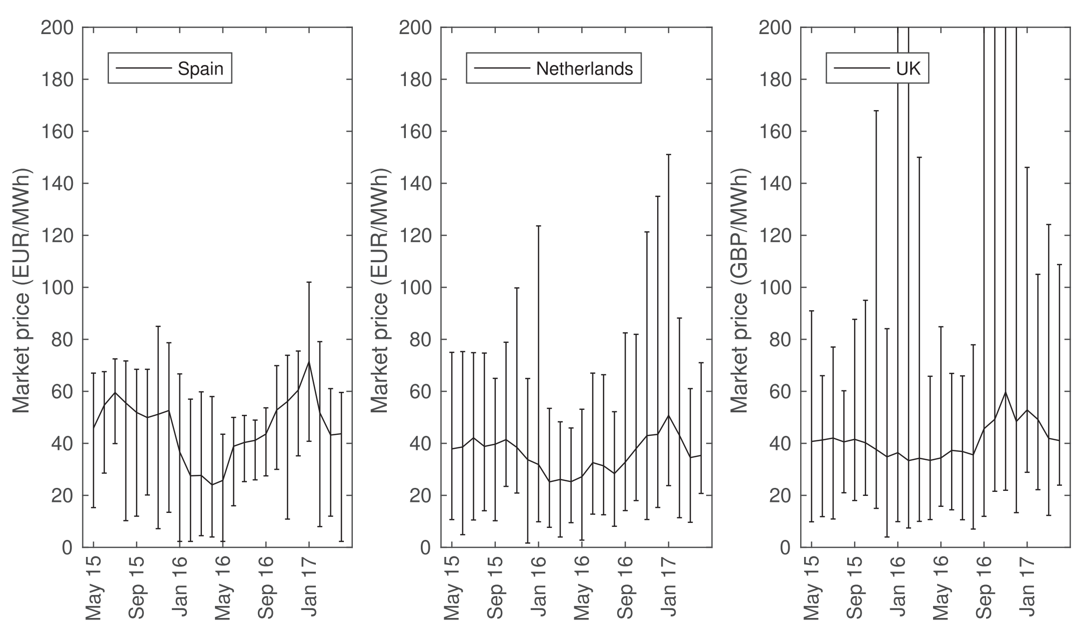

Fig. 4. Electricity prices in Spain, Netherlands and UK as monthly average and extremes [32]. Note that UK maximums up to 999 GBP/MWh are now shown in order to maintain the same scale.

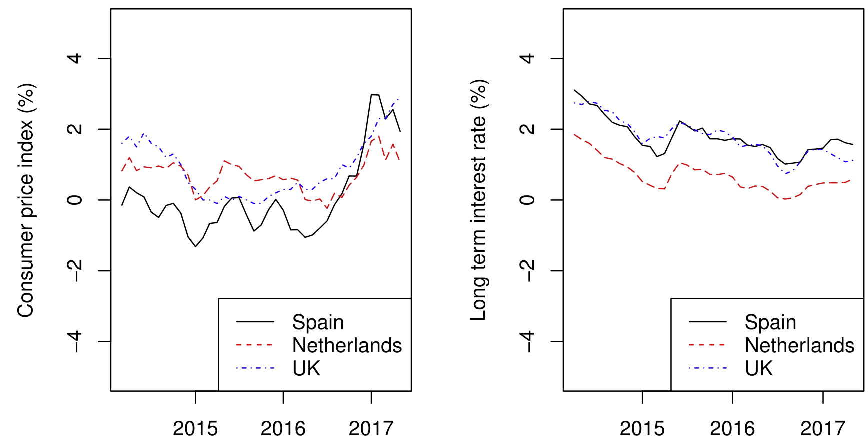

Fig. 5. Inflation and interest rates based on [33].

Table 4
Correlation of market prices p (EUR), onshore wind production e_w (MW), and wind speed v (m/s) for 2015.

Country		p	e_w	v
Spain	p	1	− 0.371	− 0.279
	e_w		1	0.535
	v			1
Netherlands	P	1	− 0.121	− 0.079
	e_w		1	0.570
	v			1
UK	p	1	− 0.145	− 0.068
	e_w		1	0.452
	v			1

history of subsidies for Spain, Netherlands and UK [27,42,43].

Simplified subsidies were applied based on the farm commissioning date of 2002. In Spain, two schemes had been available for the operator to choose: a fixed feed-in tariff of 77.47 EUR/MWh or a premium based tariff with a guaranteed rate of 75.41 EUR/MWh and an upper cap of 89.87 EUR/MWh. Both subsidy schemes were investigated separately. Although subsidy schemes are available in the Netherlands, the combination of the commissioning date and the age of the farm resulted in no subsidies for 2015–2017. In UK, the Renewable Obligation scheme were applicable for this farm with one issued certificate per generated MWh. We applied the monthly lowest auction price for the certificates recorded by the Non-Fossil Purchasing Agency [44] as a premium. With monthly revenue, corporation tax and subsidy, the cash flow is uneven as sketched in Fig. 7. The setup of the NPV analyses is summarised in Table 5.

4. Performance analysis

Different modelling approaches were compared in a first step of the performance analysis. Thereafter, the evolution of performance was analysed by discussing power curves for various conditions.

4.1. Comparison of different power curve models

A clear impact of the different wind directions can be identified in Fig. 8 for power curves obtained by filtering individual wind direction sectors in the training period. The turbine shows better performance for wind from south to east and is slightly

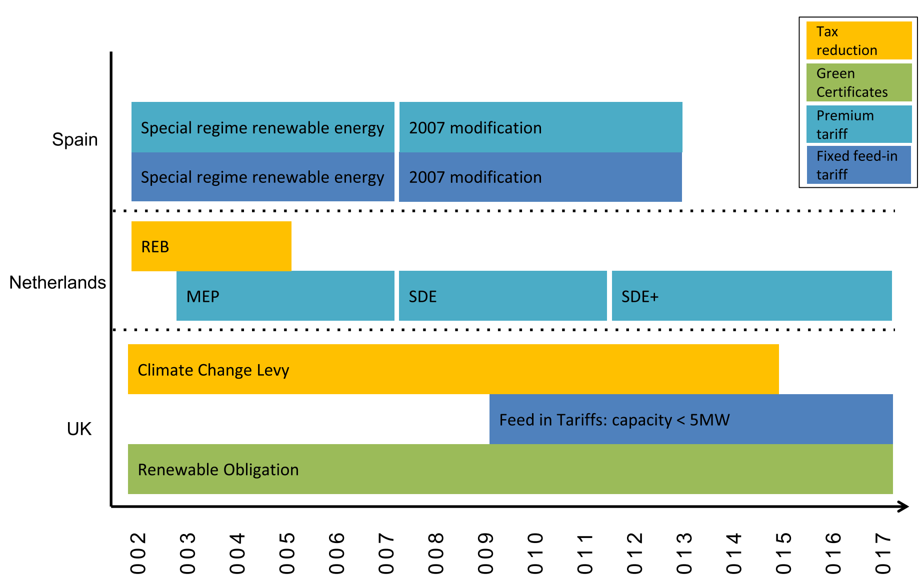

Fig. 6. Simplified history of wind energy subsidies in Spain, Netherlands and UK.

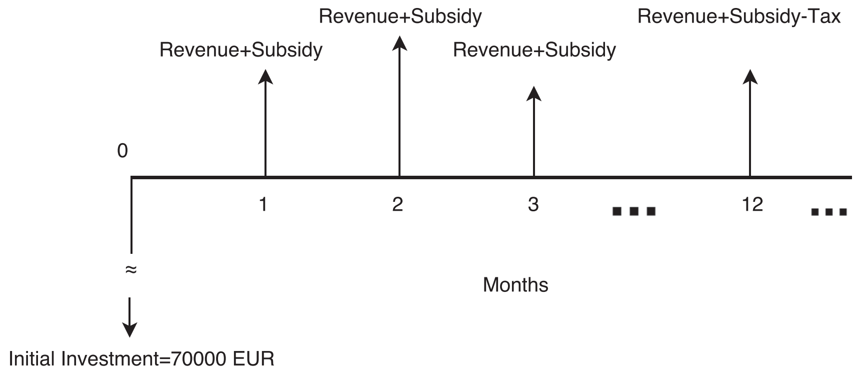

Fig. 7. Illustration of uneven cash flow set-up.

Table 5
Parameters for cash flow setup and NPV analyses.

General parameter		Definition	
Duration		May 2014 to May 2017	
t		Monthly	
N		37	
i		Monthly long term interest rate - consumer price index	
Currency		Baseline: EUR, UK case: GBP	
Setting	**Relevant month(s)**	**Cash flow**	**Details**
Baseline	1	cash-out	Blade costs: 70000 EUR
	13–37	cash-in	Monthly sum (hourly energy * hourly electricity price)
Subsidies included	13–37	cash-in	Monthly sum (hourly energy * subsidy)
Tax included	20,32,37	cash-out	Annual sum (hourly energy * hourly electricity price * profit rate * tax rate)

underperforming in wind from northerly directions. This cannot be explained by wakes or terrain slopes (cp. Fig. 1). It is possibly that this is caused by different wind shear and turbulence due to local weather and winds [45].

A seasonal variation of the performance can be seen in Fig. 9 with a comparison of quarterly power curves in the training period. The performance is lower in summer, but similarly high for winter, spring and autumn. The illustrated behaviour remains unchanged if the previously discussed density correction is applied and is also similarly visible in other years.

The prediction errors of the different univariate and multivariate models are given in Table 6 for the validation period. It can be seen; that different rankings of the models emerge for the various metrics. There is a marginal improvement for quarterly and directional power curves for all metrics except sME, though it should be stressed that these models may not satisfactorily predict the power for the entire range of wind speeds. For example, 1% of predictions are undefined for the directional power curves as they did not see certain higher wind speeds in the training dataset. The different ANFIS models show lower errors when considering temperature and wind direction for most metrics. However, there is no significant benefit of using the ANFIS model instead of the method of bins.

The ANFIS prediction errors (scaled to the turbine rated power) from Ref. [23] are added to Table 6 for comparison. It is apparent

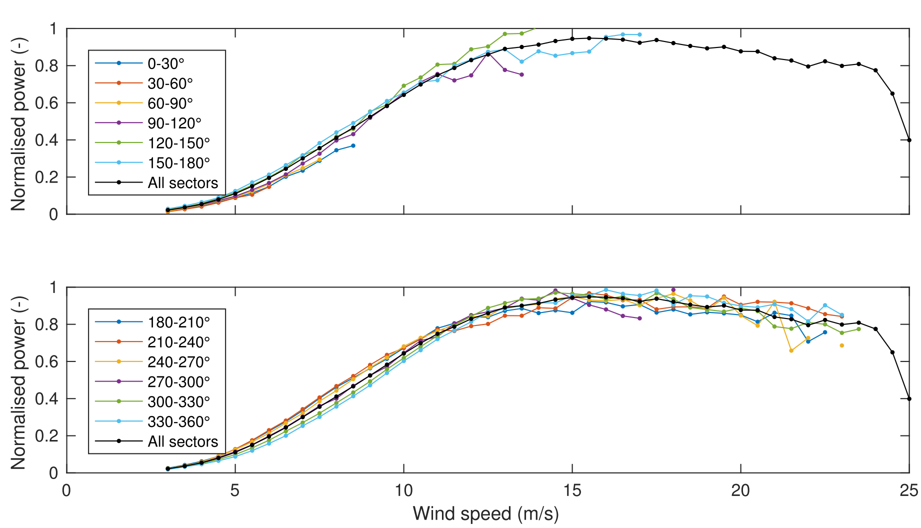

Fig. 8. Power performance for different wind direction sectors.

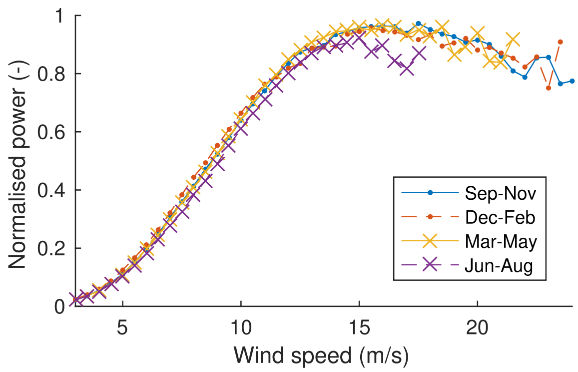

Fig. 9. Seasonal variation in power performance.

Table 6
Prediction errors of different method of bins (MOB) and ANFIS approaches (as percentage of the turbine rated power).

Model	sMAE	sME	sRMSE	sSD
MOB	3.6145	−0.4111	6.8775	6.6700
Quarterly MOB	3.4427	−0.6267	6.5605	6.1583
Directional MOB	3.0902	−0.6348	6.5983	5.9494
ANFIS a	3.4767	−0.3647	6.7972	6.7875
ANFIS b	3.4283	−0.5776	6.5470	6.5216
ANFIS c	2.9188	−0.6219	6.4825	6.4527
ANFIS d	2.8991	−1.0687	6.4304	6.3411
ANFIS in literature [23]	1.60	–	2.30	2.30

that they achieved far lower errors, although it has to be noted that this was obtained from a pitch regulated turbine and fewer data. Other research attempting to model power curves for small stall-regulated turbines showed a clearly higher sMAE of 5.3% of rated power [46].

All in all, it can be seen that the power curve of this turbine shows a large degree of spread in power output at higher wind speeds as shown in Fig. 10. This uncertainty is not sufficiently addressed by any of the models used. Accordingly, we use the simple method of bins for the subsequent part of the study.

4.2. *Performance in different conditions*

The derived reference power curve can be used to assess the evolution of the power performance. In Fig. 11, the performance is illustrated for July 2012 until April 2017 by showing the monthly deviation from the expected energy per wind speed bin. For this visualisation, the pre-processing included only filtering of invalid signals and non-operation. The maintenance interventions listed in Table 2 are marked and labelled with the corresponding number. The training period is also indicated by dashed lines. The power curve is based on the performance within this period. There are several periods with underperformance that result in a loss of up to four rated power hours per wind speed bin (yellow–red–black colour). Performance significantly better than the reference is limited (green–blue). If the icing exclusion rule is applied for this analysis, most of the underperformances disappear, as shown in Fig. 12. The remaining underperformance in May to June 2013 is probably caused by a faulty anemometer which was replaced in the subsequent month (maintenance intervention 3). A second underperformance was clearly visible in May 2015, i.e. after the blade replacement, but before the blade re-pitching (maintenance interventions 8 and 9). Noticeably, the energy loss in June to August 2015 was not as high as in May although the re-pitching did not take place before September 2015. This might be explained by the lower wind speeds in these months.

For the sensitivity study, several power curves were derived representing certain performance conditions. The first additional curve was generated for the sub-optimal pitch angle by selecting data between maintenance interventions 8 and 9. A second power curve was built for icing underperformance by using all icing events in the training period. Two further power curves were defined to analyse the effect caused by the differences in performance of wind directions, here with simplified sectors of 45° for north-northwest (NNW) and west-southwest (WSW). Fig. 13 shows the resulting power curves in the various conditions. Icing and the sub-optimal pitch angle result in strong losses in wind speeds above 10 m/s, whereas the wind direction affects mostly the lower wind speeds. It should be noted that these power curves are only intended for conducting a what-if sensitivity study, but are not necessarily accurate representations of the performance as the uncertainty is significant.

5. Sensitivity study results

The sensitivity study discusses what-if scenarios for the effects of maintenance timing, environmental conditions and country dynamics as listed in Table 7.

5.1. *Effect of maintenance timing*

Fig. 14 shows the effect of the maintenance timing in the energy generated over the two years. Here, the baseline represents a delay in the optimisation of 141 days (May to September) without any downtime. The baseline NPV, i.e. for Spain without considering subsidy or tax, emerged as 102,549 EUR. However, it should be emphasised that relative changes of the NPV are of interest in this study, as the absolute NPV value is a consequence of the assumptions taken in the cash flow setup. The baseline is compared with various scenarios of optimisation delay, additional downtime and shifting of the intervention (as listed in Table 7). Fig. 15 gives the resulting NPV for the scenarios.

It can be seen that the duration of the delay has a significant impact on both energy and NPV, but is not as dramatic as for downtime. A direct optimisation (after 0d) results e.g. in a NPV increase of 2130 EUR, whereas 90 days of downtime reduce the NPV by 15,740 EUR. Energy and NPV do not change linearly with the length of underperformance or downtime due to the varying wind resource. The relative change of the NPV per day of underperformance or downtime is shown in Figs. 16 and 17. The relative NPV change per day is approx. ten times bigger for downtime compared to underperformance.

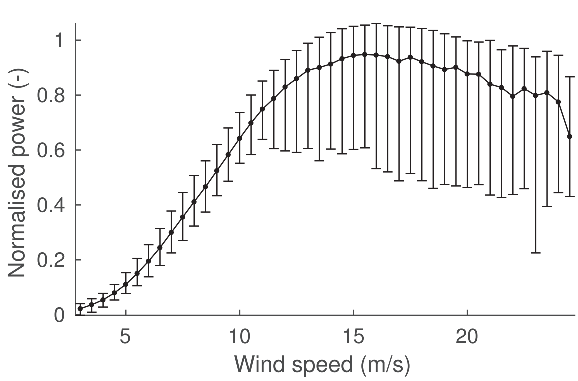

Fig. 10. Power curve uncertainty shown with 5 and 95 percentiles for each bin.

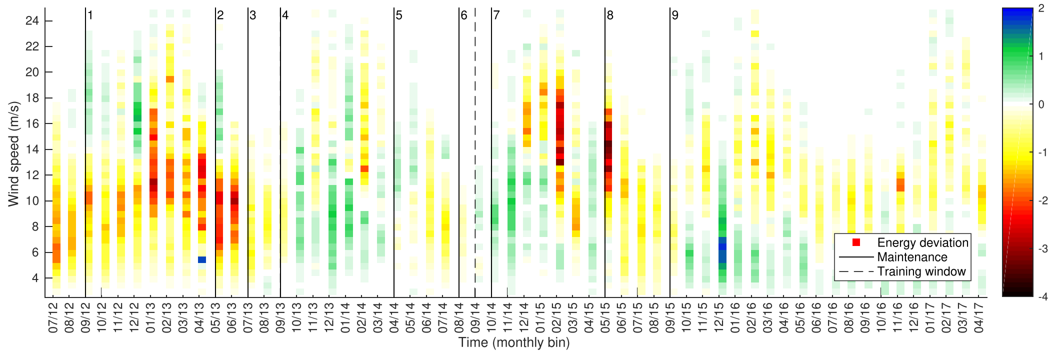

Fig. 11. Deviation from expected energy per month.

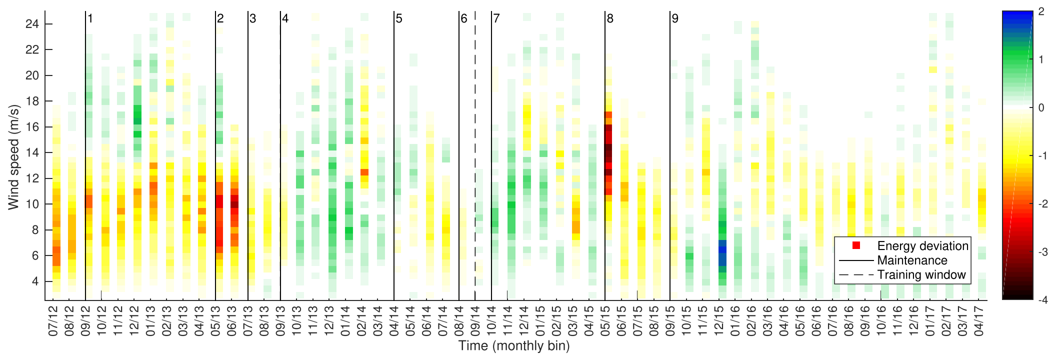

Fig. 12. Icing-filtered deviation from expected energy per month.

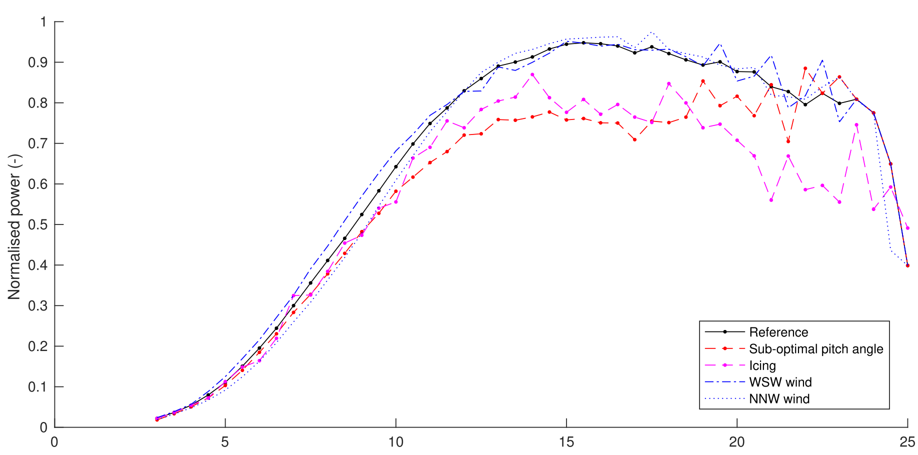

Fig. 13. Power curves for several conditions.

Table 7
List of evaluated scenarios.

Category	Scenario group	Baseline value	Tested values
Maintenance timing	Optimisation delay	141 days	0, 30, 180 days
	Additional downtime	0 days	15, 30, 60, 90 days
	Shifting of the intervention	0 months	1, 2, 3, ...12 months
Environmental condition	Icing	19.7 days	0, 26.7, 33.7, 40.7 days
	Wind direction	124/203 days WSW/NNW	327 days WSW, 327 days NNW
Country dynamics	Country	Spain	Netherlands, UK
	Taxed revenue	0%	10%, 20%, 30%
	Subsidy	no	Scheme 1, Scheme 2

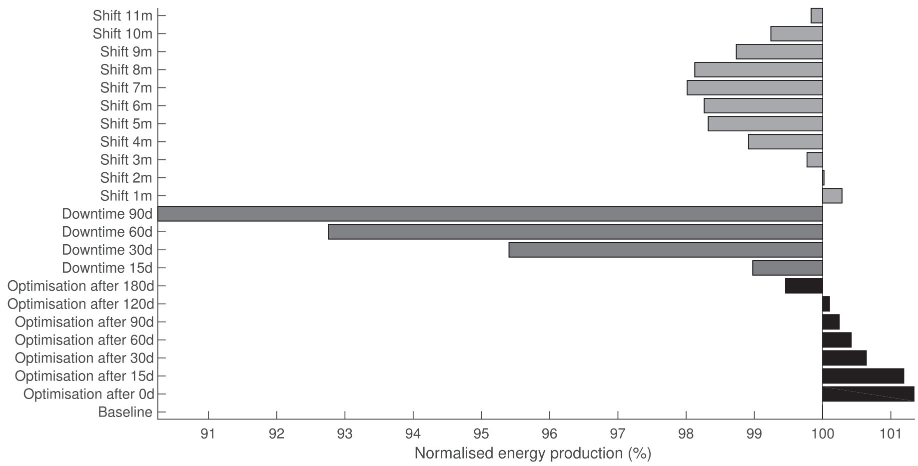

Fig. 14. Effect of maintenance timing - energy.

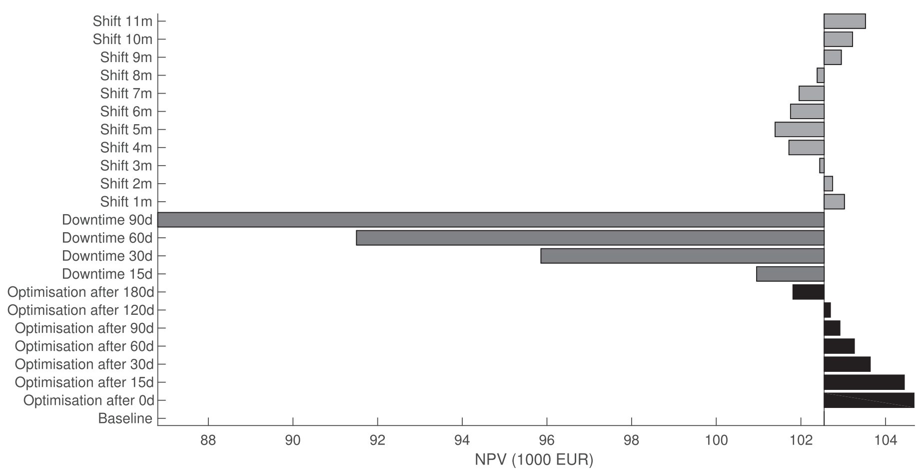

Fig. 15. Effect of maintenance timing - NPV.

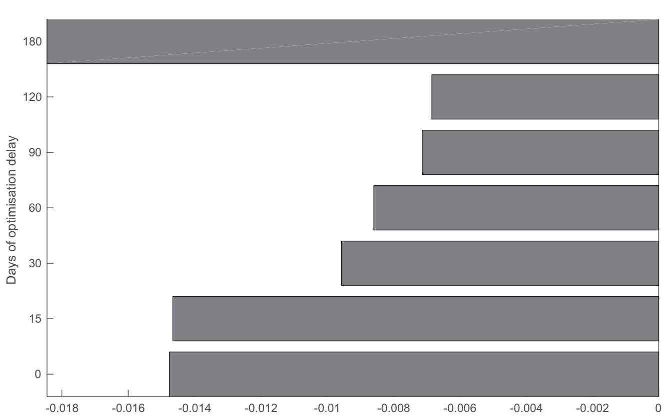

Fig. 16. Sensitivity of NPV to optimisation delay.

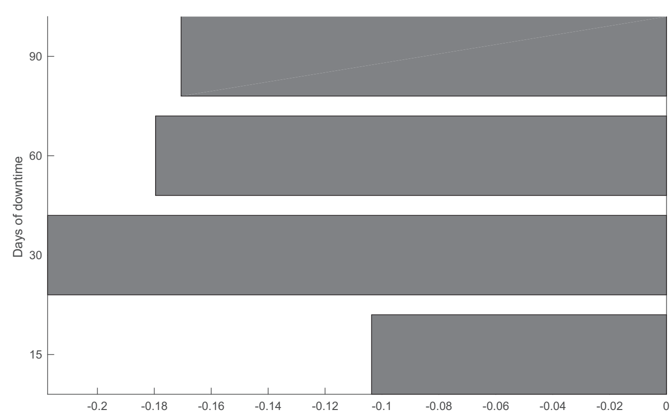

Fig. 17. Sensitivity of NPV to downtime.

If a shifting of the maintenance intervention is compared, we see that the real decision was nearly optimal based on the energy produced. Only a shift of one month (underperformance in June–October) results in slightly more energy. However, a different picture emerges if the electricity market is considered as five possible options arise here with higher NPV than the baseline.

5.2. Effect of environmental conditions

The effects of environmental variations are shown in Fig. 18 in comparison with the baseline, which represents 19.7 days of icing and wind direction fractions of 17.36% for WSW (124 days) and 28.27% for NNW (203 days). It can be seen that icing-free conditions

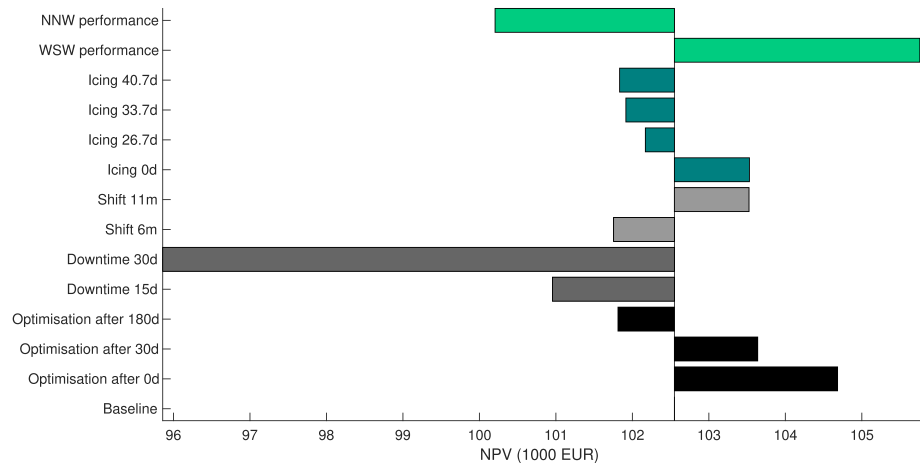

Fig. 18. Effect of environment on NPV. Selected maintenance timing scenarios added for comparison.

result in an increase of the NPV that is comparable to the maintenance timing scenario with only 30 days' delay in the optimisation. Again, it can be seen that the losses due to icing are not fully proportional to the length of icing due to the varying wind resource (relative NPV change per day of −0.0486% to −0.0139%).

The change in the performance for certain wind directions has a very strong effect. If the NNW performance is applied to all winds from NNW and WSW, the NPV is decreased to a value that is in between of 15 and 30 days of added downtime. If the better performance of WSW is used, a higher NPV is achieved than for all other discussed scenarios. The relative NPV change is however similar to the other underperformances with an NPV change per day of 0.0154% and −0.0184%, respectively.

5.3. *Effect of country dynamics*

The effect of taxes and subsidies is mostly on the baseline value for all cases as summarised in Table 8.

The relative changes of the NPV as a function of the days of delay of the optimisation are not strongly affected by the different country electricity market economics.

There is a trend to higher NPV losses per day of underperformance with lower absolute NPV for the baseline for most setups except in when comparing Netherlands to Spain. Here, the baseline NPV is higher for Netherlands, but the daily NPV loss is slightly bigger than in Spain. If the shifting of the maintenance interventions is compared for the different countries, Fig. 19, it can be seen that the ranking of the best options varies somewhat.

Table 8
For each country, the effect of corporation tax, wholesale electricity prices and subsidies on the baseline.

Country	Taxed revenue	Subsidy	NPV (1000 EUR)
Spain	none	no	102.5
	10%	no	97.9
	20%	no	93.3
	30%	no	88.7
	none	premium	214.9
	none	fixed	221.7
Netherlands	none	n/a	104.1
	10%	n/a	99.7
	20%	n/a	95.3
	30%	n/a	90.8
UK	none	no	150.7
	10%	no	145.3
	20%	no	139.8
	30%	no	134.4
	none	premium	151.0

6. Discussion

The analysis of the power production and maintenance history of the turbine investigated reveals that the performance varied significantly. Density correction is tested, but did not improve the accuracy of the predicted power curve compared with actual data. The application of a temperature and relative humidity based rule for the identification of icing events proved to match quite accurately with observed underperformance. A derived power curve using the method of bins shows a high uncertainty related to seasonal and directional effects that is also not better addressed by a multivariate ANFIS model. However, the error in the power curve is not unusual when compared with similar analysis in the literature [23,46]. The impact of underperformance due to a suboptimal pitch angle, icing and directional effects is clearly visible in separate power curves.

The financial consequences of underperformance are shown in the NPV of the cash flow. In this setting, 10 days of underperformance due to the suboptimal pitch angle result in approximately the same NPV reduction as 1 day of downtime (see Figs. 16 and 17). The current industry practice of conducting a delayed optimisation of the pitch angle could be questioned here as any initial investment for direct optimisation that is less than 2130 EUR would pay off in the case of the turbine investigated. This could be implemented by a combination of performance monitoring and blade angle determination with advanced image-capturing or unmanned aerial vehicles (drones).

There is also optimisation potential in terms of the timing of any maintenance that results in temporary underperformance. The analysis of shifting the maintenance period through the year shows that the actual timing was optimised to the seasonal wind resource trends. The financial results indicate that the optimal timing will change due to the different seasonality of electricity markets. However, this is affected by the complexity of the cash flow, the electricity market in each country, taxes and subsidies. In most configurations, a shifting to earlier spring appears to be more profitable.

The NPV sensitivity study with icing and wind directional performance variation demonstrated that these environmental effects are similarly important. In particular the performance changes for the two main wind directions require more detailed investigation. Measuring turbulence intensity and wind shear could be the first

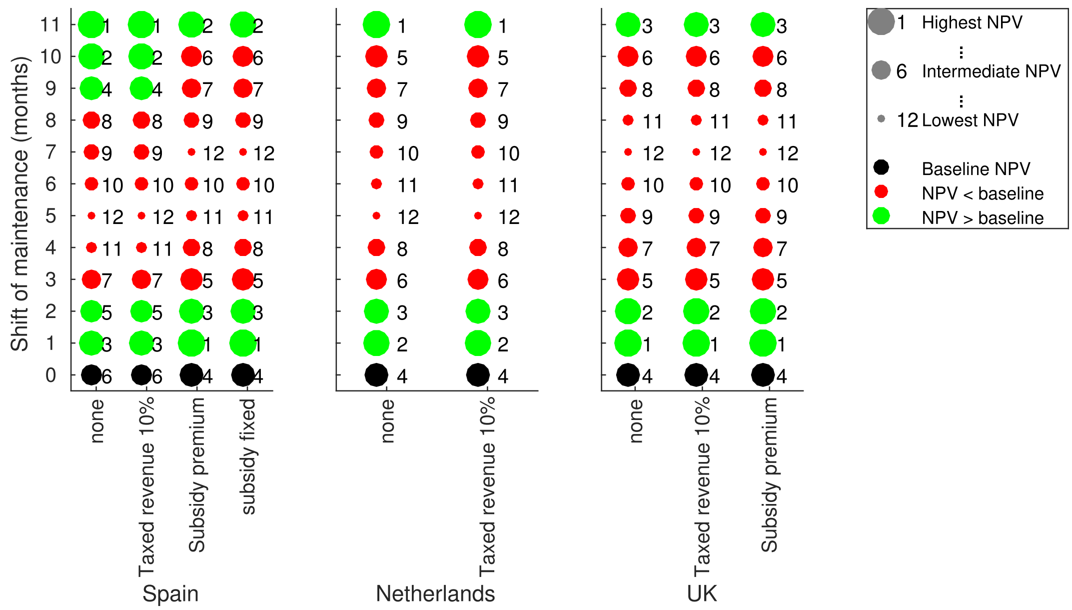

Fig. 19. Ranking of shifting options for different frameworks and countries.

step to understand the performance differences.

The comparison for the three countries highlights in addition that based on the electricity markets alone, UK and Netherlands were more attractive for the wind farm studied. If the subsidies are included, the Spanish baseline is more advantageous. However, it should be noted that the attractive Spanish subsidy scheme ended and new wind farms may rely only on electricity market sales.

7. Conclusion

The maintenance, performance and revenue of a wind farm are analysed based on the example of one wind turbine. The impact of a sub-optimal pitch angle resulting from a blade replacement is shown by highlighting the energy losses and net present value (NPV) reduction in a cash flow analysis that considers the replacement costs and energy sales from two years. A relative NPV change of approx. −0.01% per day of the underperformance is identified. It is found that the NPV is similarly sensitive to icing and changes of the turbine's performance with different wind directions. Downtime, however, causes a relative reduction of the NPV per day that is more than ten times larger. An analysis of the timing in the year indicates that shifting the blade replacement to spring could be more cost-effective. A study with different settings of corporation tax and subsidies in Spain, Netherlands and UK shows that these changes mostly affect the value of the baseline NPV, but not the relative trends for underperformances and losses. However, the ranking of options of timing of the maintenance differs slightly for the countries and if subsidies are included.

All in all, this study highlights the complexity of a single maintenance decision. The methodology used could act as a template for future evaluation of decisions and their impact in performance and revenue.

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