# Wind Energy Prediction Bias in European Onshore Wind Projects – an Investor Survey

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## 1. Introduction

To further investments in utility-scale wind projects, investors in projects should be making their desired return. A key determiner in whether a project is a good investment is if it can achieve expected power production throughout its life. All, who participate in the wind industry, desire to know how projects perform against estimates made during the investment stage.

Power production estimates are created by consultants in the form of an energy yield assessment (EYA) wherein the annual energy production (AEP) is calculated. We often refer to the long-term AEP estimate as the 10 or 20-year $P_{50}$. This is the prediction that has 50% chance of being exceeded. This and related downside scenarios are used to finance and then set performance expectations for the life of a project.

At some point, these projects have their performance expectations revisited. Following a year in operation, one can perform post-construction yield assessments (PCYA) using actual generation data. These assessments can be done by the investor or operator themselves, or otherwise, they can be performed by the same consultants used to make the EYA's. PCYA's are usually more accurate than EYA's as many of the pre-construction modeling uncertainties have been removed from the analysis. These PCYA's can be compared to the original EYA to determine bias.

Through the years, there have been questions and investigations into the accuracy of pre-construction EYA's. It is generally accepted that over time there has usually been a negative bias in project performance, or otherwise, projects have tended to underperform. In the United States, there has been very public dialogue on this topic. National Renewable Energy Labs (NREL) documents the history of this discussion in a recent publication (Lee and Fields, 2021). NREL shows that within the US, while there has been large negative bias in the past, there has generally been improvement over time.

In Europe there have been fewer publicly available studies on the topic of $P_{50}$ bias. Recently, several consultants have produced self-validation studies. In 2019, DNV-GL reports $P_{50}$ validation result of 96.9% in Great Britain and 95.0% in Ireland for a study based on 87 and 25 projects respectively (DNV-GL 2019). In 2020, UL reports that UL-DEWI, their European arm, had a 94.0% performance ratio in a study of 50 projects (UL 2020).

With the most visible information on this topic coming from the self-reporting by the firms producing EYA's, it is interesting to get the view into EYA $P_{50}$ bias from the investor point of view. To address this, Hendrickson Renewables (Hendrickson) has performed a survey of investors with interests in

77 onshore European wind projects and asked the simple question – how did projects performed against initial EYA $P_{50}$ expectations?

The objective of this study is to produce information from the investor's perspective about the magnitude of $P_{50}$ bias. This is not an evaluation of any consultant but rather a view from the side of companies relying on consultant EYA's. It is hoped this study will be used as basis into further investigations into plant performance and can further the continual improvement of EYA predictions within the wind industry.

## 2. Study Description

This study is modeled after an approach successfully used in the United States from 2006 to 2012 by DNV-Kema (DNV-Kema 2013) where the primary data source came from an independent survey of companies owning and operating US wind farms. Our primary goal was to evaluate the accuracy of EYA's by comparing them to PCYA's prepared during operation stages.

Companies with investor positions in onshore European wind farms were asked to provide project performance data anonymously. Hendrickson aggregated this and is presenting the results in this paper.

Hendrickson had no role in performing any of the involved EYA's within this study.

### Requested data

The following data were requested of the participants:

- Country
- Commercial online date
- Wind turbine nameplate (MW)
- Project nameplate (MW)
- Project average wind speed (m/s)
- Date EYA produced
- Pre-construction EYA $P_{50}$ (GWh)
- Post-construction PCYA $P_{50}$ (GWh)
- Years of data in PCYA
- Observed availability (%)
- Observed curtailment (MWh)

There were several parties who provided data where availability and curtailment had been normalized to a standard value within the PCYA. For these, we asked for the pro-forma availability and curtailment values that the PCYA's used.

### Study characteristics

Figure 1 and Tables 1 -5 show study demographics by the requested dimensions. Note that not all participants provided information for all fields, which explains why the count doesn't tally to the study total in each table.

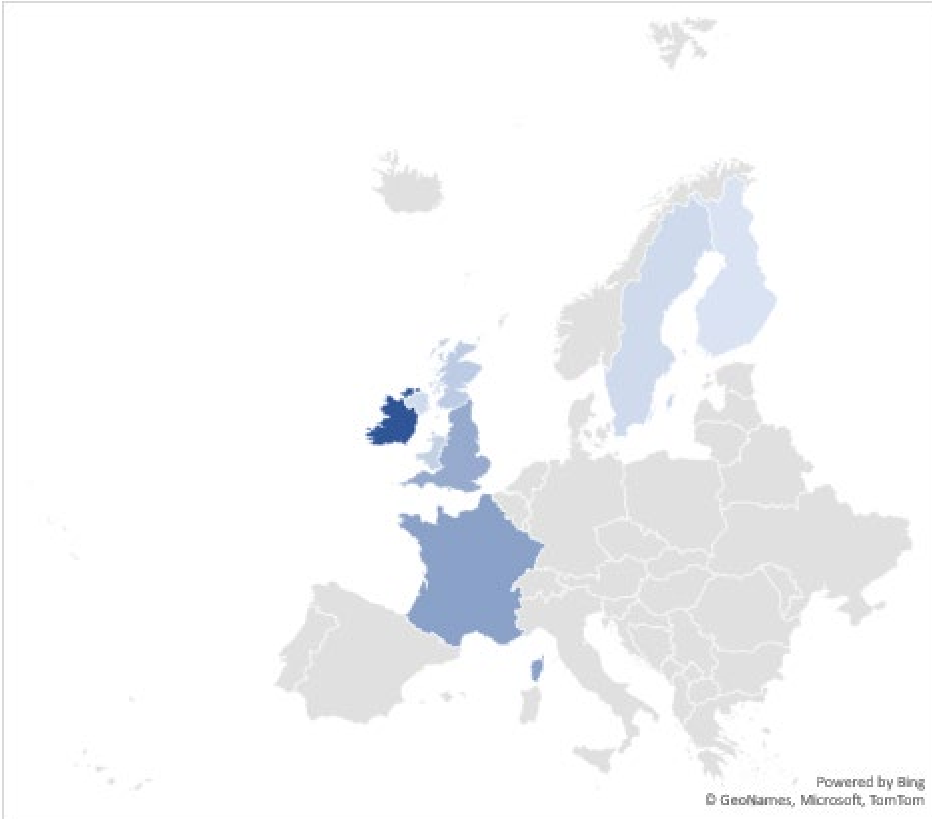


**Figure 1.** Countries in study – shaded by participation

| Country | Count |
|---|---|
| England | 13 |
| Finland | 1 |
| France | 15 |
| Ireland | 31 |
| Northern Ireland | 3 |
| Scotland | 6 |
| Sweden | 3 |
| Wales | 5 |
| **Total** | **77** |

**Table 1.** Data received by country

Data were provided from 8 countries.  There are 58 projects sourced from the British Isles with 15 projects from France.

| WTG Nameplate (MW) | Count |
|---|---|
| 0.50-0.99 | 3 |
| 1.00-1.49 | 0 |
| 1.50-1.99 | 1 |
| 2.00-2.49 | 39 |
| 2.50-2.99 | 9 |
| 3.00-3.49 | 9 |
| **Total** | **61** |

**Table 2.** Data received by turbine nameplate

Turbine nameplate data were collected. Projects with turbine nameplate of 2.0 to 2.5 MW made up 39 of the reported 61 turbines.

| Project Nameplate (MW) | Count |
|---|---|
| 0.00-9.99 | 8 |
| 10.00-19.99 | 21 |
| 20.00-29.99 | 8 |
| 30.00-39.99 | 3 |
| 40.00-89.99 | 4 |
| **Total** | **44** |

**Table 3.** Data received by project nameplate

In terms of project size, 21 of the reported 44 projects were 10 to 20 MW size.

| COD Year | Count |
|---|---|
| 2006 | 1 |
| 2007 | 0 |
| 2008 | 0 |
| 2009 | 0 |
| 2010 | 2 |
| 2011 | 0 |
| 2012 | 2 |
| 2013 | 6 |
| 2014 | 6 |
| 2015 | 7 |
| 2016 | 11 |
| 2017 | 20 |
| 2018 | 14 |
| 2019 | 5 |
| 2020 | 3 |
| **Total** | **77** |

**Table 4**. Data received by COD year

Data were provided from projects with COD as early as 2006. A large group of projects, 45, came with COD's in years 2016 to 2018.

| Project Average Wind Speed (m/s) | Count |
|---|---|
| 5.5 | 2 |
| 6.0 | 9 |
| 6.5 | 13 |
| 7.0 | 9 |
| 7.5 | 6 |
| 8.0 | 14 |
| 8.5 | 9 |
| 9.0 | 2 |
| 9.5 | 2 |
| **Total** | **66** |

**Table 5.** Data received by project average wind speed

Data were collected across a range of wind speeds. In terms of IEC wind classification for average wind speed, 9% made up Class IV, 42% made up Class III, 36% made up Class II and 12% made up Class I.

## 3. Considerations and Limitations

### Data provided "as-is"

A primary consideration in this study is that the data are provided "as-is". Hendrickson did not perform the EYA's or PCYA's. In some cases, the data were provided normalized in a way to preserve confidentiality. As such the results are presented at face value.

### Sample Size

It should always be mentioned that sample size is usually a limiter in this type of study. This survey is relying on 77 projects. There is a possibility that these projects might have some bias relative to its population. The effect of sample size was addressed in the 2015 validation study created by Vaisala (Stoelinga, 2015) where they used a Monte Carlo simulation to estimate confidence intervals of any wind farm validation study as a function of sample size. Using their work, a study this size is estimated to have a 95% confidence interval around the P50 bias of 2-3%.

### Availability normalization

Roughly half of the projects submitted for this study provided PCYA results having availability data normalized to a standard pro forma value. The average pro forma availability for provided projects is 97.0%. The remaining projects in the study provided an estimate based on actual project availability or were otherwise normalized to a system forecast derived from actual availability. The average availability of projects that submitted availability estimates was 96.9%. Figure 2 shows the distributions of availability from PCYA projects with availability forecasts derived from observed project data.

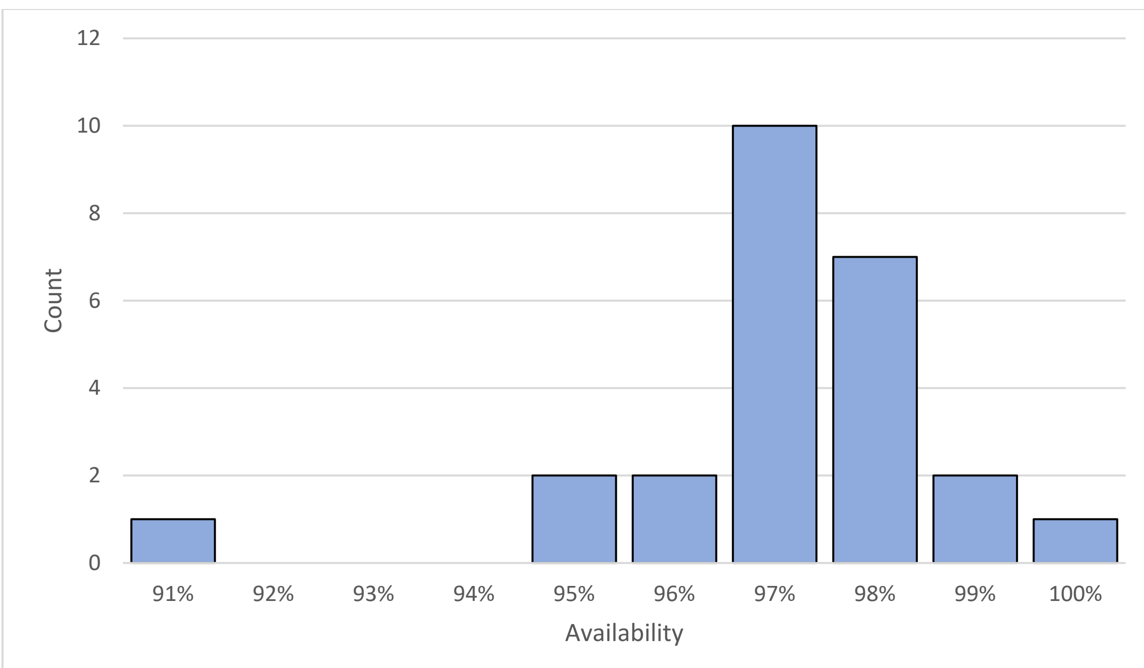


**Figure 2.** Project availability distribution

Since observed and pro-forma availability estimates were quite close, we made no further treatment. Hendrickson does not expect results to change much due to availability treatment. It's just noted so that the primary $P_{50}$ bias results can be considered as partially treated for availability.

Also, for commercial and technical reasons, availability data provided by different parties is not always consistently calculated. For this study, it was assumed availability information represented all in project energy availability.

### Curtailment normalization

Only five projects provided information about observed curtailment. However, the participants indicated that survey data was given with curtailment backed out. In theory, curtailment is excluded from this survey. This is consistent with the way most EYA consultants report on curtailment and is customary practice in PCYA validation studies.

But, there is uncertainty in the curtailment normalization process. If curtailment is high, there can be potential for it to be underreported, which would translate into a source of bias of this study.

This risk was discussed with several study participants. Anecdotal information was shared about observed fleet curtailment. Based on provided information about observed curtailment amounts and expected accuracy of the curtailment normalization process, it was determined that while this uncertainty exists, it is unlikely large. At most, it introduces a potential 1-2% bias which wouldn't affect much the primary conclusions.

### Long feedback cycle

Another key consideration is that $P_{50}$ bias of EYA's can be considered a moving target. There can be a four-year lag between when an investment decision is made using prediction technology of the time and when enough data returns from projects that ultimately get built. The cycle may go like this using a convention of years before and after commercial online date (COD).

- COD minus 1 year – Investment decision made relying on an EYA
- COD – project gets built
- COD plus 1 year – first year of operations, not enough data
- COD plus 2 years – second year of operations, previous year was stabilizing
- COD plus 3 years – enough data to perform a PCYA

In the time the initial investment decisions are made and when a PCYA may be performed which tests the skill of the EYA relied on for the investment decision, a lot could have changed in the prediction landscape. Hub heights have increased. Turbine dimensions have scaled. Investments are in new geographies or in new markets which might bring their own challenges. This creates an environment where there are constant demands on the system to map what is understood from our predictions made several years ago to the technical challenges being faced now. New risks are being added which might also come with bias. This was discussed by Hendrickson in a 2019 presentation, "P50 Bias Update – Are We There Yet?" (Hendrickson 2019). Hendrickson uses a concept called outer risks to describe new technical challenges not considered in past feedback studies which might introduce new bias.

## 4. Results

There were 77 projects wherein we could test how the projects performed against the original EYA's. Figure 3 shows this data.

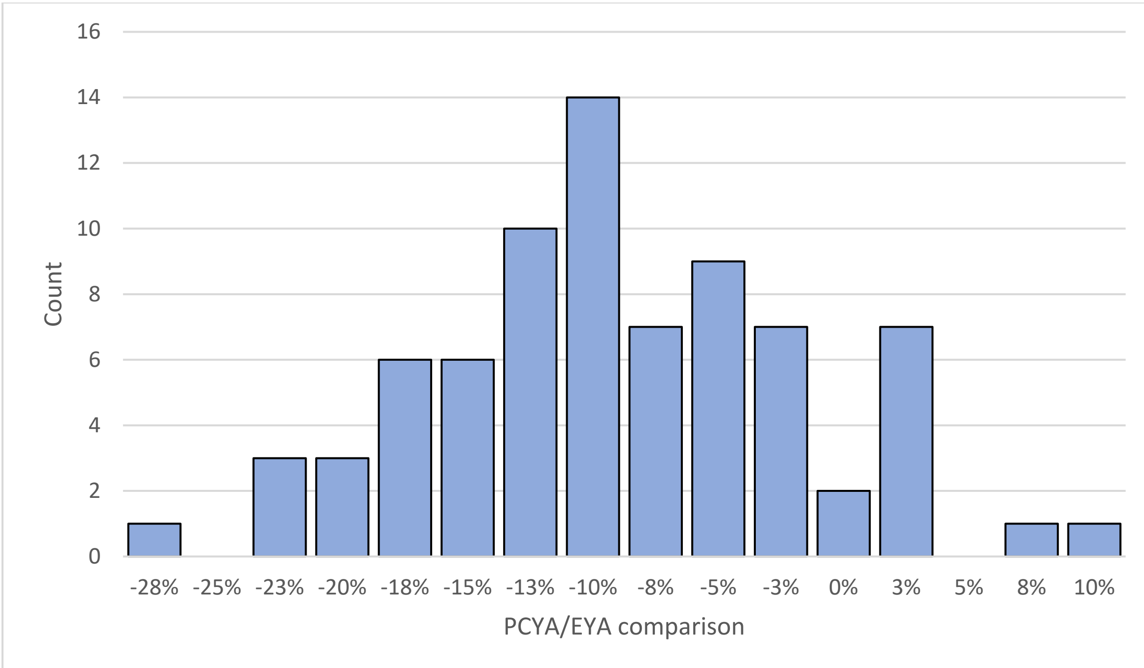


**Figure 3.** Project performance for all data

The median or $P_{50}$ bias from this data was -8.9%. If a project were performing at or better than its preconstruction expectations set by the EYA, data would be at or greater than 0%. From this data only 11 projects or 14.3% of projects achieved EYA $P_{50}$ predictions or better.

The standard deviation of this dataset is 7.3%. We often associate standard deviation of error with uncertainty. The error distributions shown are made by comparing EYA's to PCYA's, which both have an uncertainty estimate. It can be inferred then that uncertainty, of the long-term EYA should be better than the 7.3% standard deviation shown.

### Filtering for recent data

Because it is presumed that consultants are improving with time, it is interesting to filter this data further for more recent periods. We limited the full dataset to only projects where COD was 2017 or later. There are 42 projects in this database. Figure 4 shows this data.

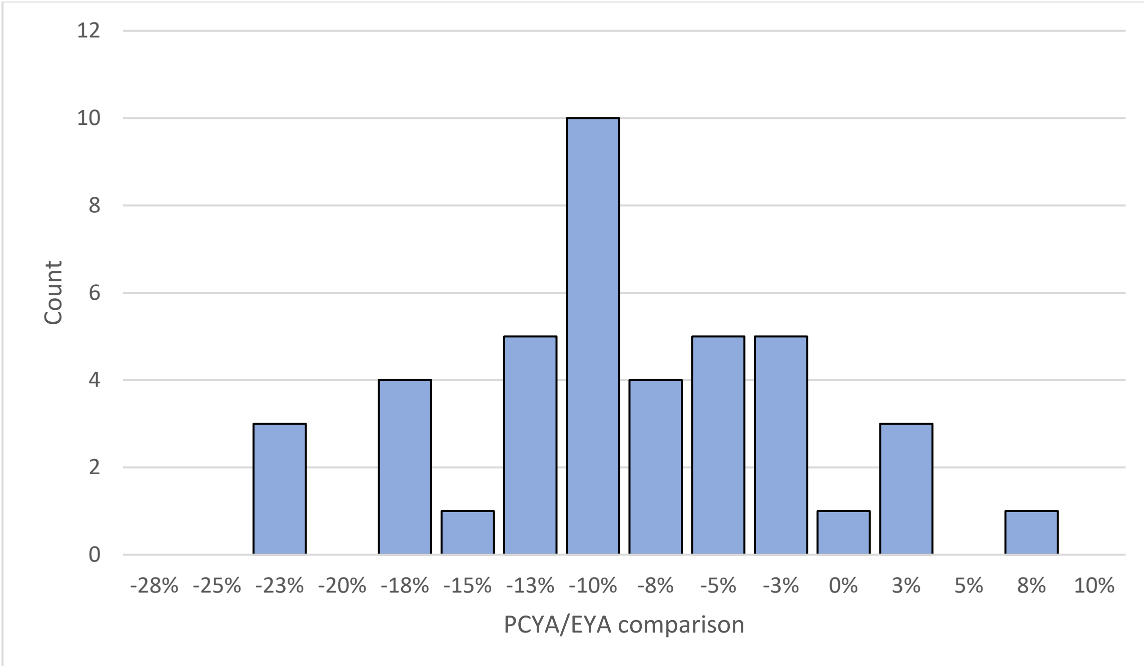


**Figure 4.** Project performance for COD is 2017 and later

The median or $P_{50}$ bias from this, more recent data is -8.8%. Just 5 of the 42 projects, or 11.9%, achieved or surpassed their $P_{50}$ EYA expectations. There is little statistical difference between the most recent projects and the whole database.

The standard deviation of this dataset is 6.8%.

### Bias over time

To examine this further, we looked at the relationship of $P_{50}$ bias over time. Figure 5 shows this data in box and whisker format. Project COD's ranged from 2006, where the database contained a single project through 2020, where 3 projects had enough data to perform a PCYA. There are 77 projects in this dataset.

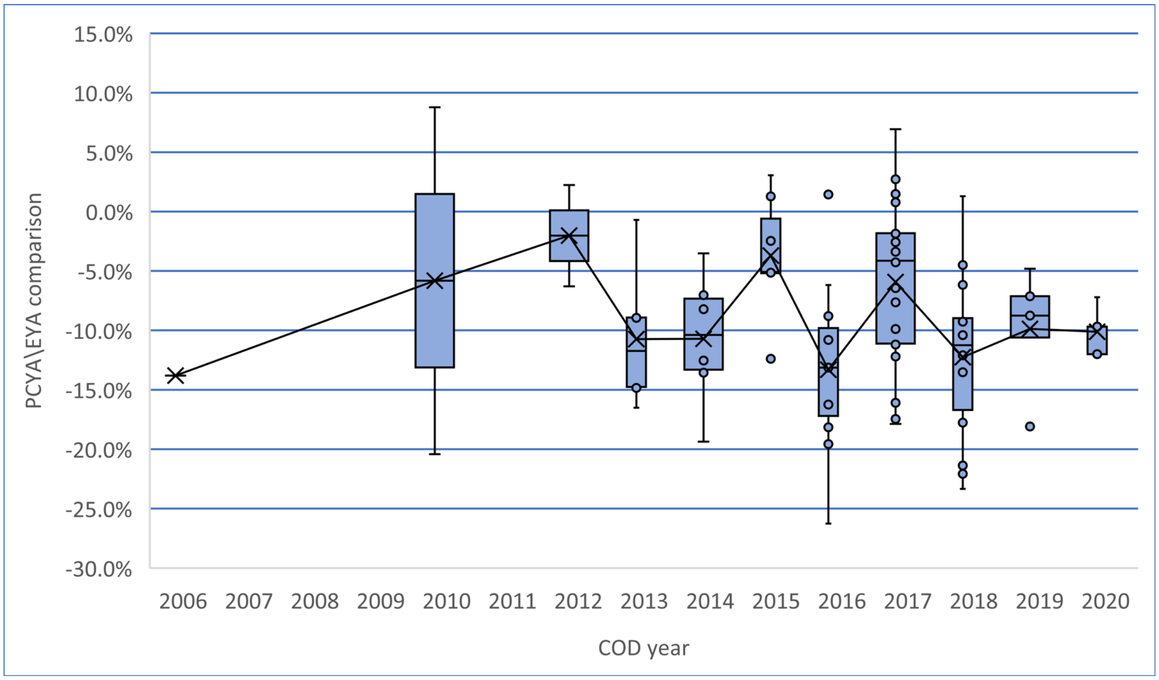


**Figure 5.** project performance by COD year

This view of the database shows no meaningful improvement in predictions over time.

### Wind turbine nameplate

PCYA/EYA data was also binned by WTG nameplate. This is shown in Figure 6. Of the 77 projects in the entire database, 61 projects self-reported nameplate.

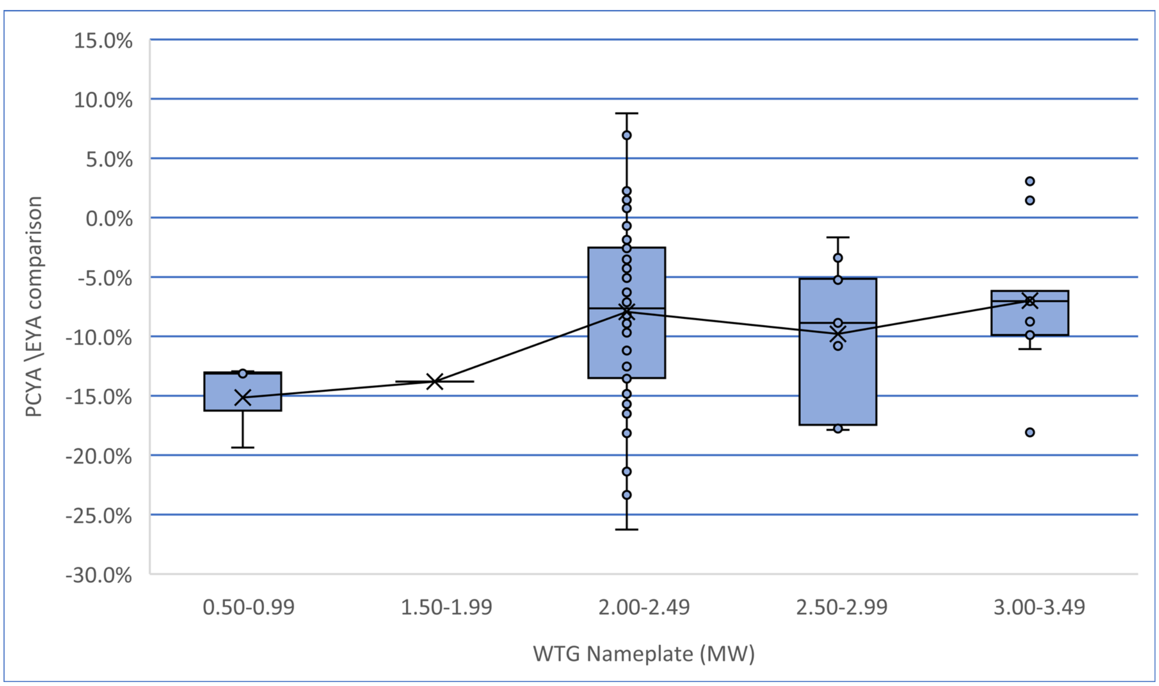


**Figure 6.** project performance by turbine nameplate

Most projects fell within the 2MW to 2.5 MW turbine nameplate range where the median bias was -7.6%. There were only four projects below 2 MW. The apparent worse performance in these categories might be statistical sampling. It is interesting that there does not appear to be a drop off in performance as the turbines have increased in scale. Theoretically, the larger turbines will come with larger rotors and more complex modeling and measurement approaches to simulate properly. Apparently, larger turbines do not necessarily mean less accurate predictions.

### Project nameplate

An attempt was also made to segregate data by project nameplate. These results are shown in Figure 7, binned in roughly 10 MW bins. There were 44 projects where this information was self-reported.

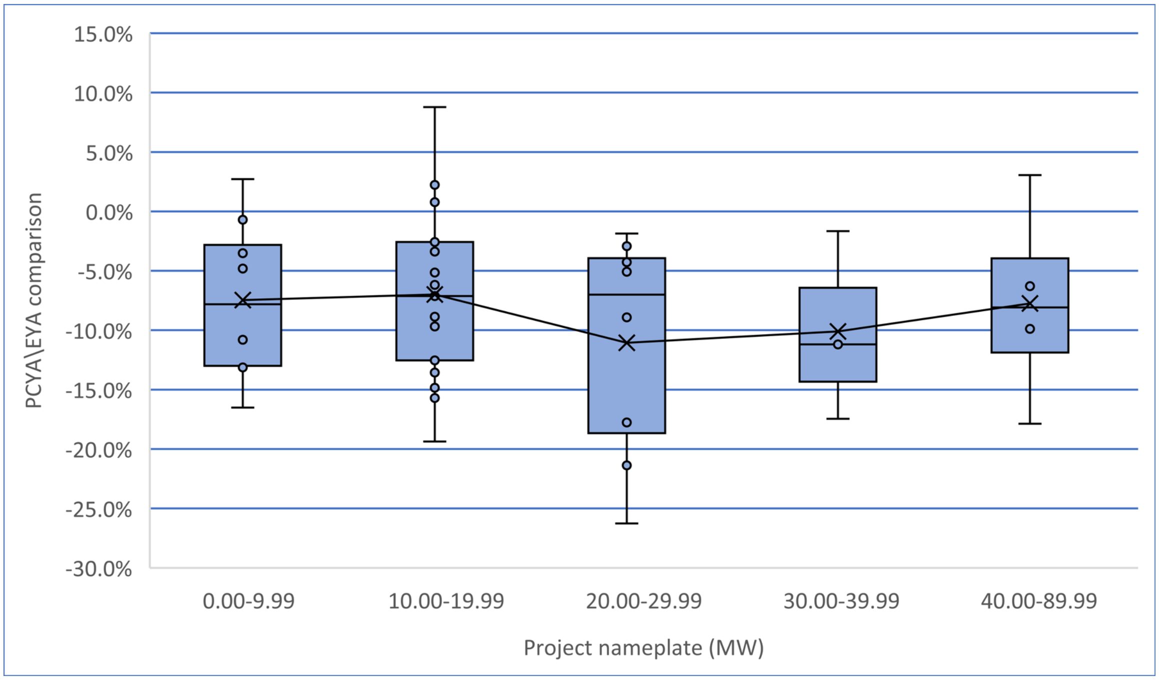


**Figure 7**. project performance by project nameplate

There is not a clear trend in $P_{50}$ bias by nameplate. Roughly half of the data, 21 projects, were collected in the 10 MW to 20 MW bin which shows a median bias of -7.1%.

### Project average wind speed

It is interesting to test if there is a relationship in $P_{50}$ bias to wind speed. From the participants, project average wind speed data was asked for. There were 66 projects that provided this information. This data is shown in Figure 8 in box and whisker form and in Figure 9 in scatterplot form.

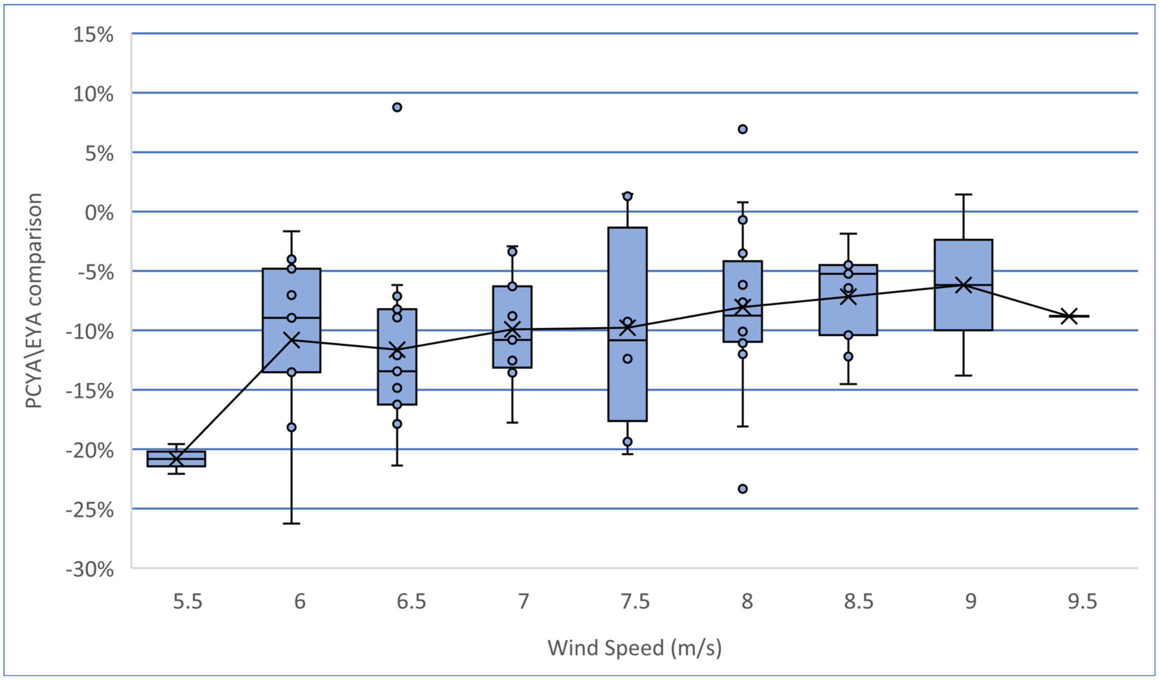


**Figure 8**. Project performance by wind speed (box and whisker)

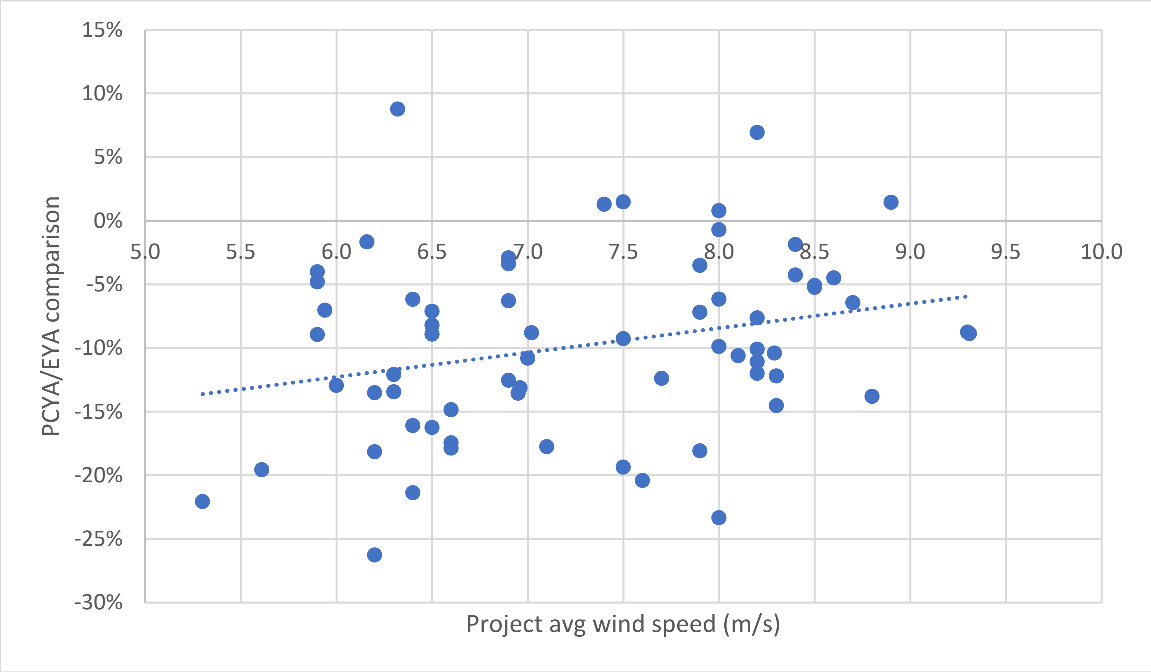


**Figure 9.** Project performance by wind speed (scatterplot)

Sorting data by wind speed appeared to draw out one of the stronger relationships that might relate to $P_{50}$ bias. This result is interesting to the author and suggests that projects with lower wind speeds are more likely to have higher risk than higher wind speed projects.

It is worth highlighting that this relationship might relate to a statistical concept of wind energy sensitivity. This idea is familiar to wind assessment practitioners and derives from the non-linear nature of a power curve. At higher average wind speeds, more time is spent in the controlled or rated part of the power curve. During these times, higher or lower winds don't change the output of a turbine. On the other hand, at lower wind speeds, a wind turbine's output is quite sensitive to changes in wind speed. This creates more risk in lower wind speed projects with much larger percent of time spent with wind speeds in the sensitive part of the power curve. This added risk shows up as higher uncertainty that goes into computing probability of exceedance values such as $P_{75}$, $P_{90}$ or $P_{99}$.

If this observed relationship continues to play out, this could suggest that there is some inherent bias, still untreated in the industries measuring devices, the most common of which is still the anemometer. Further investigations into measurement related wind speed biases, especially at low winds, is recommended.

### Wind speed build-out over time

It is plausible that as the windiest sites get built out that lower wind speed projects are more available and more likely to be built. If this were true, it potentially could partially explain the apparent lack of improvement over time as shown in Figure 5. Figure 10 shows the relationship of project average wind speed to COD year.

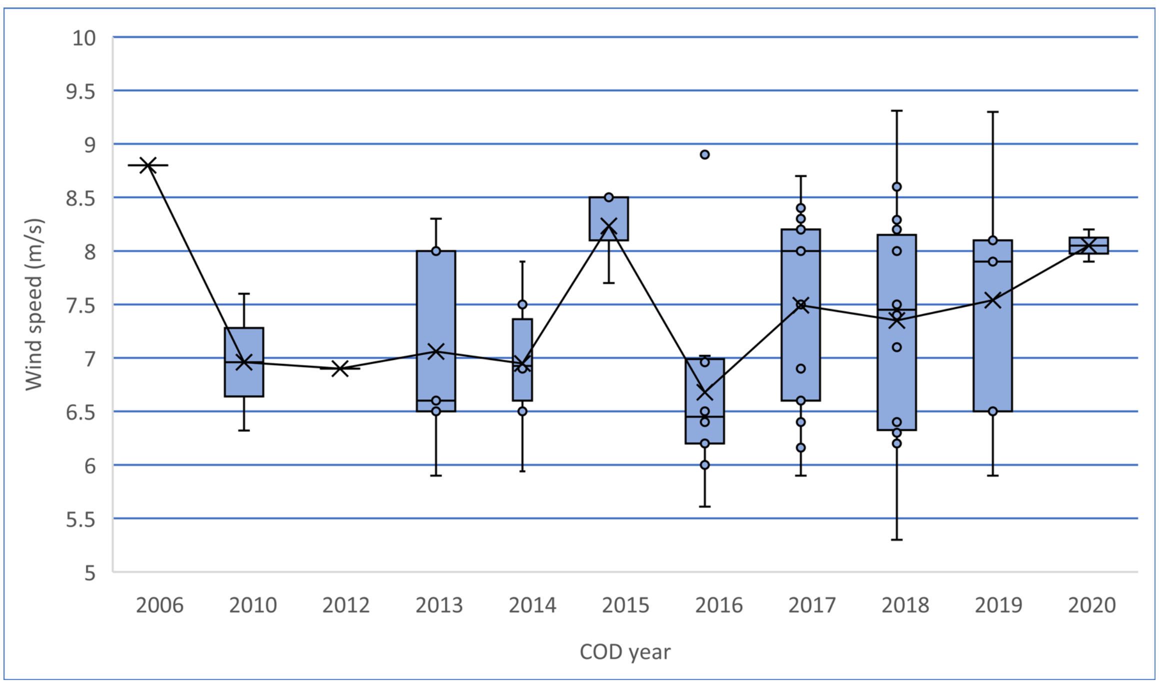


**Figure 10.** Average wind speed over time

The data does not reveal this. If anything, winds speeds appear to slightly improve. Perhaps this is related to higher hub heights or expanded utilization of available regions. It does not appear that low wind speed bias along with the tendency to build more sites that have lower wind speeds explains the lack of improvement with time shown in Figure 5.

### Performance by country

Performance by country is also available. Figure 11 and Table 6 show this data. Relationship by country could come from several sources. If wind speed is a factor, as discussed previously, it might be the case that certain countries might tend to build out lower wind speed sites. Average wind speed of projects where wind speed was provided is also shown in Table 6. Other factors such as availability and curtailment trends could also cause variability between regions.

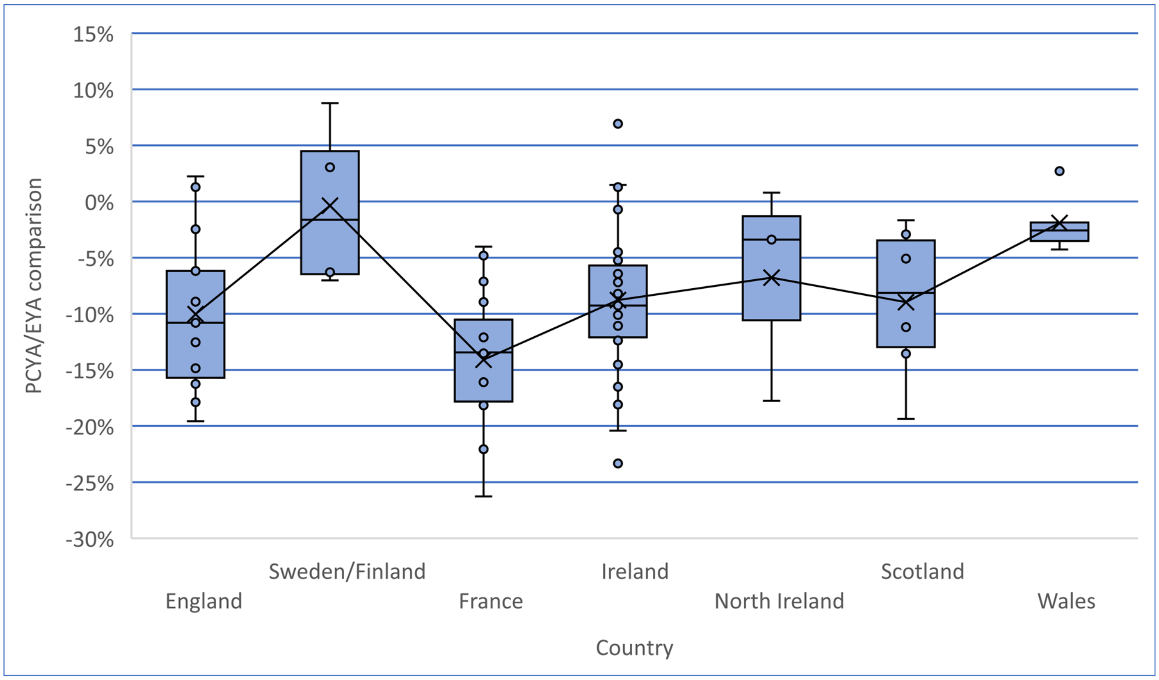


**Figure 11**. Project performance by country

| Country | Count | PCYA/EYA | Avg. Wind Speed (m/s)* |
|---|---|---|---|
| England | 13 | -10.8% | 6.6 |
| Sweden/Finland | 4 | -1.6% | 6.5 |
| France | 15 | -13.4% | 6.2 |
| Ireland | 31 | -9.3% | 8.1 |
| Northern Ireland | 3 | -3.4% | 7.3 |
| Scotland | 6 | -8.1% | 7.2 |
| Wales | 5 | -2.6% | 8.3 |
| **Total** | **77** | **-8.9%** | **7.3** |

**Table 6**. Project performance by country. Shaded rows indicate less than 10 projects and lower confidence. *Wind speed data was not provided for all projects.

Country data with these sample sizes are likely inconclusive, especially for the countries with smaller sample size. It might be important that there is a 4.1% difference between France and Ireland, two countries with larger representation. However, these biases are within the predicted 95% confidence interval suggested in Vaisala's validation study (Stoelinga, 2015).

## 5. Conclusion

This work represents an independent survey of investors in onshore, European wind projects with heavy representation in the British Isles and France. The purpose of this study was to create a view, from the investor side, into how projects are performing. Participants provided data from 77 onshore wind projects, built primarily in the last 10 years, with more than half coming from the last 4 years.

The results show that there does appear to be systemic underperformance of projects with respect to their EYA's. Median $P_{50}$ bias is -8.9%. There is very little improvement when filtered to recent years. Projects with COD of 2017 and later had median $P_{50}$ bias of -8.8%.

There were very little observable trends with respect to project and turbine nameplate. It was comforting that within the data, newer and larger turbines did not come with additional underperformance.

There appears to be a relationship with respect to project average wind speed. Lower wind speed projects tended to perform worse.

### Feedback and diligence

The purpose of this paper is ultimately to give investors more information about the projects they are investing in. Feedback is also provided to the technical community that bears responsibility to improve. This feedback cycle is unfortunately quite long. We are using projects from years ago to inform decisions about today. It's always valid to ask the relevance of this information compared to what's happening in the markets now. Technology progresses. Processes innovate. It may be that the models used by consultants have already accounted for some of what shows up as shortfall in this dataset. The due diligence process should be living and continually seek to reconcile what is being done now against what has been done in the past.

## 6. Acknowledgements

The author would like to thank the generous companies who provided data that informed this study. It is recognized this is sensitive data and not easy to share.

## 7. References

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