Correlation in power curve measurements

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Correlations can help significantly to decrease uncertainty when doing averaging or results by means of simultaneous and redundant measurement systems. This poster explains the theoretical basis under this reasoning as well as an example of real application on a DEWI/ACCIONA cooperative research project.

Power Curve Tests: investments are worth?

Most of the wind farm owners struggle with the decision of executing power curve tests on their wind farms. The investment is not marginal (met masts installation, sensors, project execution, etc.) and the return of this investment is not always evident. One and all know that the Power Curve test is critical on the financial model and checking it through a real test should be almost a must for every owner when so many millions are rolling. The fact of not having any power curve tested in a wind farm can make any further root cause analysis impossible if real underperformance is detected in operation because SCADA data power curves have not enough precision when the problem requires fine tuning. Checking the real performance against guaranteed levels is considered, for many stakeholders, another critical reason to implement a power curve test.

These reasons are for major wind farm owners sufficient to afford the investments; however the uncertainties (often incorporated into the contractual guaranty algorithms) make some companies be sceptic about the legitimacy of results because, especially on low-wind sites, uncertainty can be not abnormally larger than 6-7%.

Uncertainty: where is the fat and how to reduce it?

IEC [1] identifies most of the uncertainty contributions. It is widely known that Wind Speed plays a predominant role on the low range of the power curve while Electrical Power becomes significant on the rated power range (Fig.1 and Fig.2). There are standard practices in the industry to reduce uncertainty:

- Utilization of high-class and range-fitting sensors
- Calibrations on high-performance labs
- Best practices on mountings
- Extended campaigns to collect a highly representative database

However, many stakeholders don't consider to make proper use of averaging, correlations and independency as the most powerful tools for uncertainty mitigation.

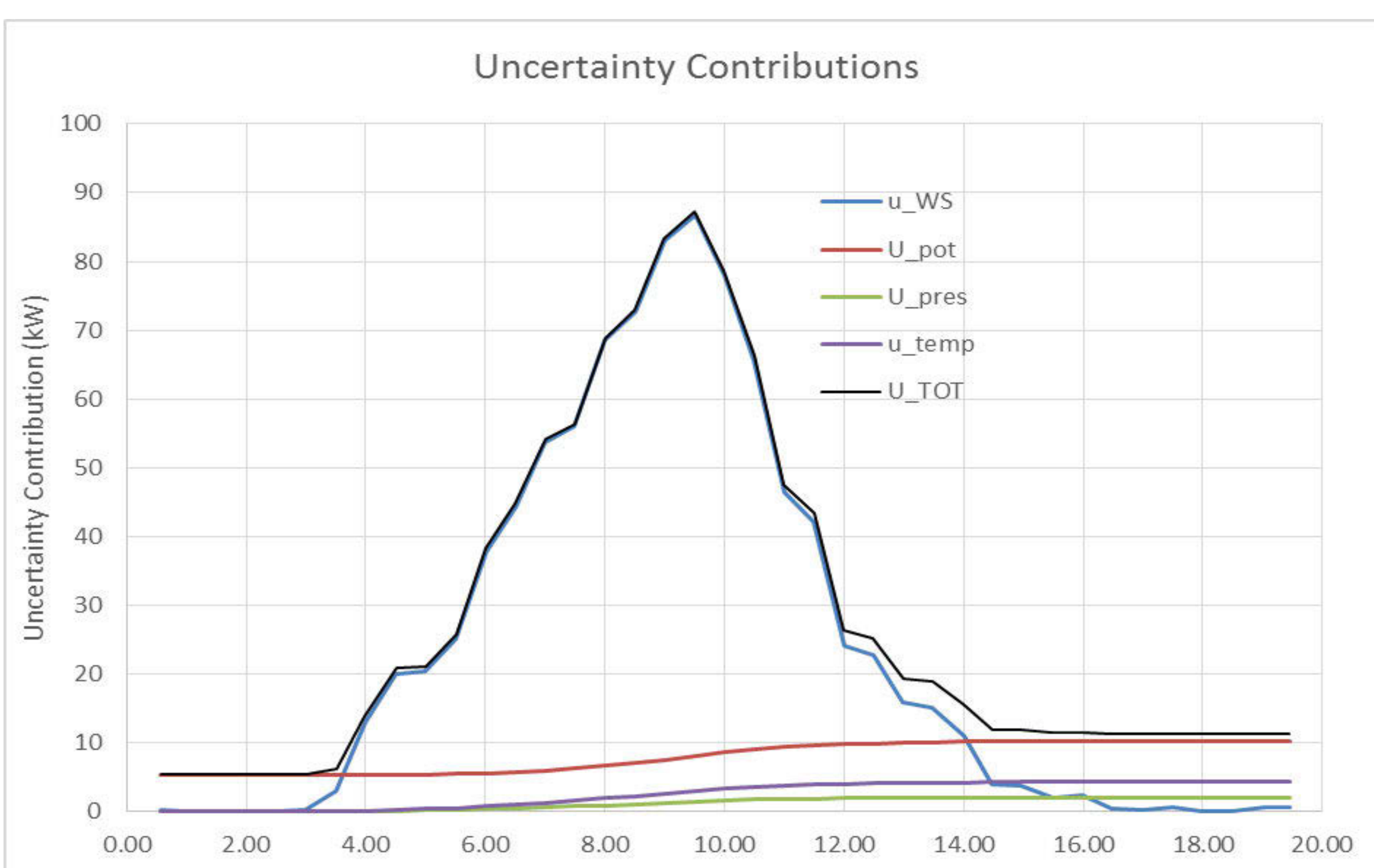

Fig.1: Typical Binned uncertainty contributions (kW) versus wind speed (m/s) for a representative power curve: [2 MW wind turbine, TFC advance (class 0.9) anemometer, flat terrain]

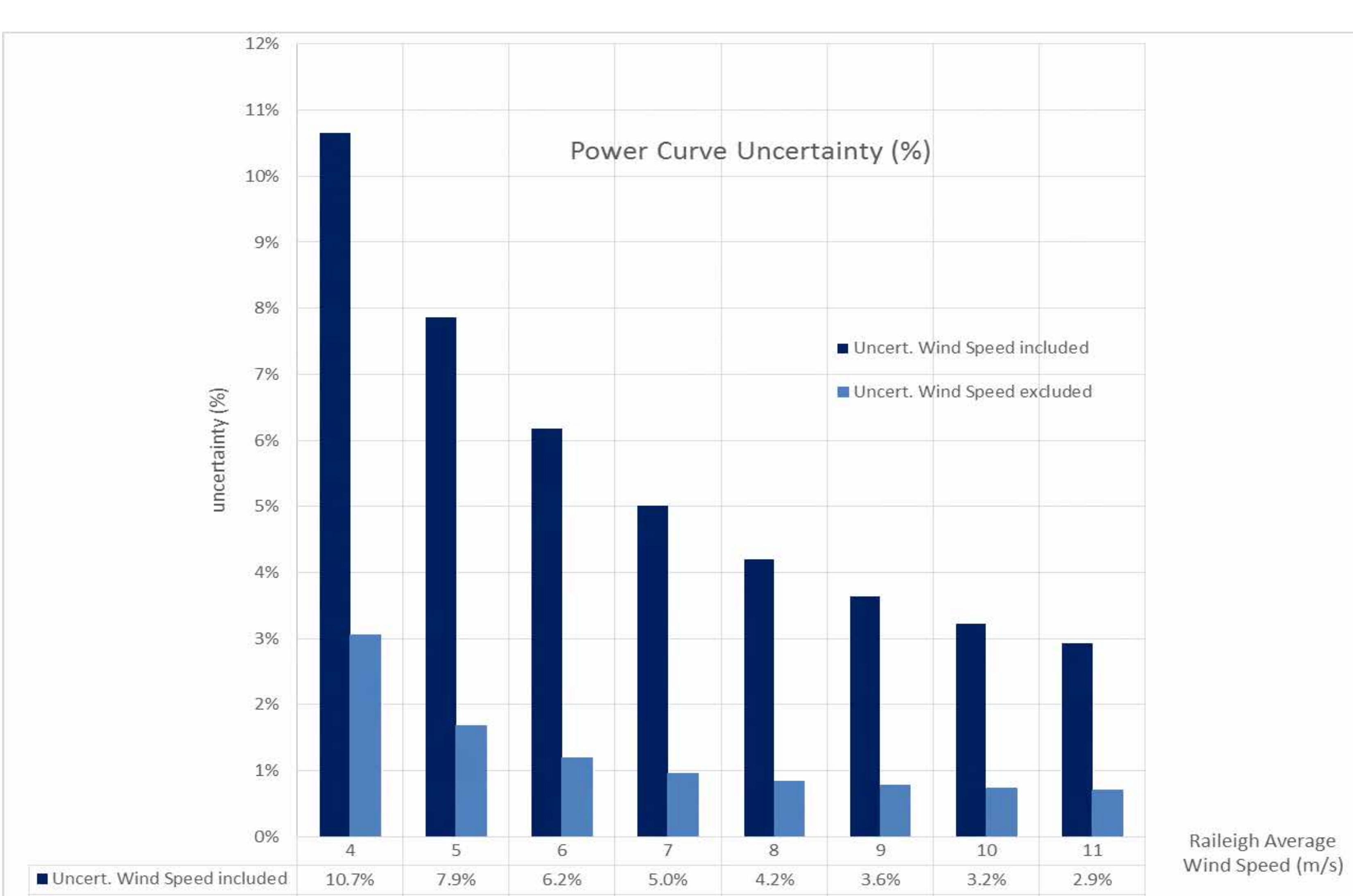

Fig.2: Relative power curve uncertainty (k=1) with and without wind speed uncertainty vs average wind speed for Rayleigh distribution (m/s) for a representative power curve: [2 MW wind turbine, TFC advance (class 0.9) anemometer, flat terrain]

[1] IEC 61400-12-1 Ed.1: Power performance measurements of electricity producing wind turbines, December 2005
[2] EA-4/02: Evaluation of the Uncertainty of Measurement in Calibration, September 2013

Averaging as the straight way to increase precision

Combined uncertainty when several parameters are influencing, is calculated according to the following formula [2]:

$$u_c^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} c_i u_i \, c_j u_j \, \rho_{i,j}$$

$$c_i = sensitivity$$

$$u_i = uncert$$

$$\rho_{i,j} = correlation$$

The correlation parameter equals 1 when parameters are fully dependent and 0 when they are independent. For the simpler case (addition) C=A+B:

$$u_C^2 = u_A{}^2 + u_B{}^2 + 2u_A u_B \, \rho_{i,j}$$

It is possible to prospect how uncertainty can be reduced averaging results of several Power Performance Tests (from 1 to 20 tests) introducing different correlation factors. The results are shown in Tab. 1. These results clearly show how averaging can contribute significantly to reduce uncertainty depending on the correlation.

Tests ongoing on Wind Farm Gostyn II

The main question therefore orbits around this correlation factor and how it could be characterized. In view of this rationale, ACCIONA and DEWI are working together in a cooperation project diving deep on correlation-covariance characterization by means of redundant systems on 2 neighbor wind turbines mixing different instrumentation setups on one single U-shape meteorological mast (Fig.3). Consequently, there are six different measurement combinations with different degrees of dependency.

	CUMULATED UNCERTAINTY(%)					
# PPM	0 Totally independent	0.2	0.4	0.6	0.8	1 Totally dependent
1	5.0	5.0	5.0	5.0	5.0	5.0
2	3.5	3.9	4.2	4.5	4.7	5.0
3	2.9	3.4	3.9	4.3	4.7	5.0
4	2.5	3.2	3.7	4.2	4.6	5.0
5	2.2	3.0	3.6	4.1	4.6	5.0
6	2.0	2.9	3.5	4.1	4.6	5.0
8	1.8	2.7	3.4	4.0	4.5	5.0
10	1.6	2.6	3.4	4.0	4.5	5.0
12	1.4	2.6	3.4	4.0	4.5	5.0
14	1.3	2.5	3.3	4.0	4.5	5.0
16	1.3	2.5	3.3	4.0	4.5	5.0
18	1.2	2.5	3.3	3.9	4.5	5.0
20	1.1	2.4	3.3	3.9	4.5	5.0

Tab.1: Accumulated uncertainty for up to 20 Power Performance Measurements (#PPM) for different correlation factors considering a common 5% uncertainty per individual test.

Fig.3: Hard time on the muddy Gostyn II Wind Farm. The picture shows installation of the different measurement combinations on the U-shaped mast. December 2015.

Conclusion:

This project targets to define the different dependency factors in order to use correlation/covariance as a powerful tool to decrease uncertainties on power curve tests without inflating testing costs.

This not necessarily linked to the number of turbines to be tested (what should, in any case, contribute to reduce uncertainty) but also the use of redundant systems on single tests. For example, and focused on Wind Speed as the most influencing parameter, using redundant anemometers from mixed models and calibration facilities.