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A new analytical framework to improve risk quantification and optimize measurement campaigns

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Introduction

The bankability is one of the most important aspects in the wind energy production projects. Bankability is based on one major point : reliability. The more the prediction is reliable, the more the banks will be ready to invest in a project. That's why we have to be able to estimate the uncertainty of an annual energy production. This uncertainty is due to impredictability of climate, uncertainty on the turbines' yield, but also uncertainty on the predicted wind flow calculated by CFD softwares. These softwares solve Navier-Stokes equations at each gridpoint of a map, and so the discrete solution is not perfect, not certain.

The aim in a pre-construction campaign is to have measured data from some measurement devices (met masts and ground based LiDARs for example) and this way know the real wind flow at these points. But how can we build a law of uncertainty on the other map points? This will be explained in the future of this document.

Let us define the backround of the following explanations. In a future wind farm site, there are some measurement points. For each point, we consider it once as the reference point, and we look at the measured values at the others points, considered as targets. And we do this for each measurement point.

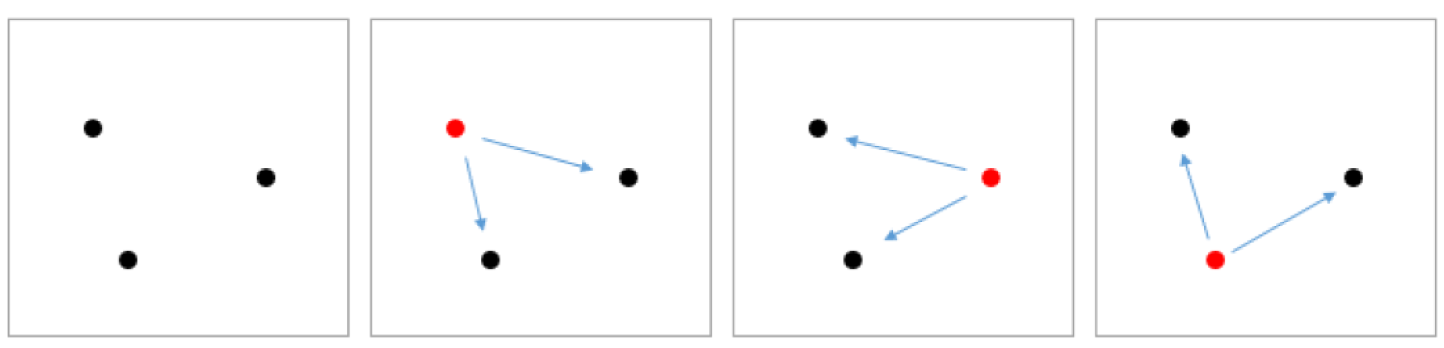

Figure 1: **Different steps of the measurement of uncertainty: each measurement point is taken once as a reference**

First observations

The first step in building this uncertainty model is quantifying the uncertainty σ itself. We define it as the standard deviation on the difference of the values of speed-ups (ratio of target to reference wind speed) found with CFD simulation and from the measured values of the sensors on site (like WindCubes or met masts). If k is the speed-up, and N the length of the time stamp, we have

$$\sigma = \sqrt{\frac{1}{N}\sum_{meas=1}^{N}\left((k_{meas}-k_{CFD})-(\overline{k_{meas}-k_{CFD}})\right)^2}$$

Since it is impossible to cover all the locations during the measurement campaign, we want to use the extrapolation method to subdue this problem.

The first observation we dit is that the maximum of σ allways appears before 2000 data points (about 2 weeks), so we are sure to have an upper bound of the real uncertainty after only two weeks.

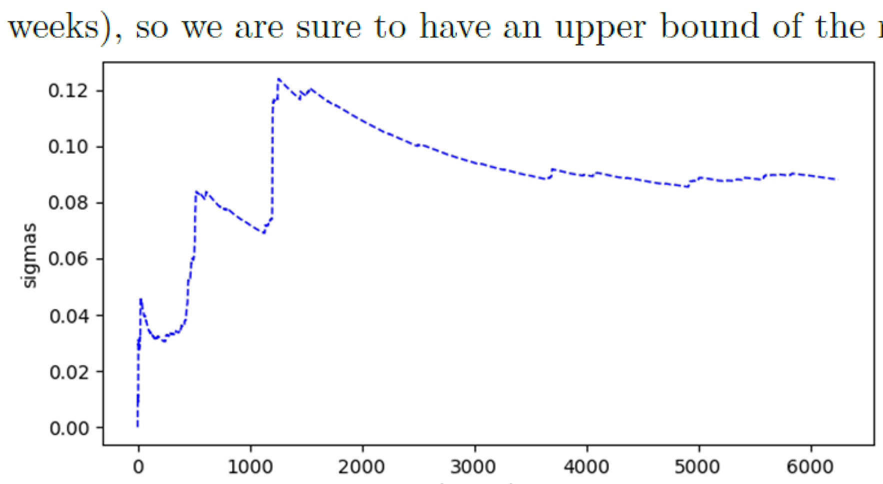

Figure 2: **Evolution of σ over time**

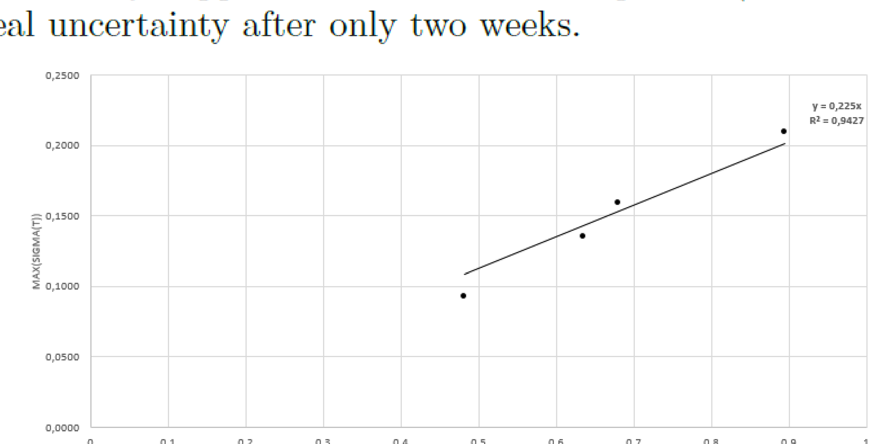

Figure 3: **One of the first observations about σ_{max}**

Then, we have thought about a linear law for extrapolation (σ versus distance) because it came up in our first projects, and with a good correlation coefficient of approximately $R^2 = 0.94$ (for the maximum of σ over time for example).

Using this law to estimate uncertainty - algorithm

Once we have noticel this linearity, next step is to use the idea of target and reference to build the model and implement the extrapolation law. As a reminder, a reference is a point where we have a sensor and a target is a point in the space where we want to extrapolate σ values from the reference.

Clearly uncertainty at the location where the measuring instrument is placed will be zero and as we move away from this location it varies according to the extrapolation law. Choosing references as well as targets to be at locations where we have a measuring instrument will help us in cross-correlating concurrent data from different references (met masts or remote sensors). Hence when we talk about a reference from now on we will consider all other references as targets for it.

We are interested in finding reference-specific laws because the wind resource around each reference is different. Although the ZIX value (value giving the roughness complexity of the terrain, from 0 to 4) for a site may be small (0 or 1) it is entirely possible that wind resource around two references is greatly different. Since our approximation is a linear all we have to do is find the slope of this linear law (α) for each reference to find our reference-specific laws (the reference-specific law is: $\sigma = \alpha * distance$).

The intercept of the linear law is zero because as discussed above the uncertainty at the reference is zero (at d=0).

For each reference we first find α in all the periods with concurrent data by using σ_{max} or σ_{period} (this is the last value of the measured period, like 0.09 on figure 2) and applying $\alpha = \sigma/d$ where d is the distance between the target and reference. Actually the most appropriate is to use σ_{period} because this tells the uncertainty reached at the end of the measurement period, but σ_{max} gives a upper value. This calculation of α is done for all possible targets for a particular reference and then an average is taken over all these values of α. Doing this for all the references gives us reference-specific laws in this concurrent period. Similarly, this is done for all the periods.

While estimating alphas for all references in a period we add to the uncertainty by averaging and hence it becomes important to estimate this uncertainty on uncertainty ($\delta\alpha$) to make our model more accurate. The value of $\delta\alpha$ is calculated as the standard deviation on the α values for all the targets corresponding to a particular reference.

To make this more accurate, we try to quantify variation of $\delta\alpha$ against the angle. The idea here is that we know the uncertainty on α but actually only in the direction of the target; in the other directions we are less sure about it. For one reference, uncertainty on α increases from $\delta\alpha$ in the direction of a target to $1.5 * \delta\alpha$ in the opposite direction in a linear fashion (arbitrary value for now). To take into account this variation we consider bins across each reference and find $\delta\alpha$ for each of these bins.

It could be discussed why we do this on $\delta\alpha$ and not on α but actually it doesn't really matter because we are considering $\alpha + \delta\alpha$ in the final mapping.

For more than one target we take the minimum in each bin. This will give us a list of $\delta\alpha$s for each reference.

However it is possible in some cases that a reference point has a measuring instrument that is recording data for more than one period. In this case, we do a weighted average over the alphas of this reference across all the periods using the number of data points as the weights. The idea here is that more number of data points will give us less uncertainty. The value of $\delta\alpha$ is then weighted using number of data points in each bin across the periods. Lets consider a project where we have three periods (with respectively N_1, N_2 and N_3 data points) and one of reference say a met mast is recording for all three periods. Its α and $\delta\alpha$ are computed as (considering the measurements independant):

$$\alpha = \frac{N_1\alpha_1 + N_2\alpha_2 + N_3\alpha_3}{N_{tot}};\ \delta\alpha = \sqrt{\frac{N_1^2\delta\alpha_1^2 + N_2^2\delta\alpha_2^2 + N_3^2\delta\alpha_3^2}{N_{tot}^2}}$$

After analyzing all the periods and all the references in them, we move on to create an uncertainty map that shows the spatial variation of these reference-specific laws applied together at each grid point. We use the following law for creating the map :

$$\sigma(x, y) = \min_{i\,\in\,ref}\left((\alpha_i + \delta\alpha_i) * d_i\right)$$

where d_i is the distance between the point (x,y) and the reference i.

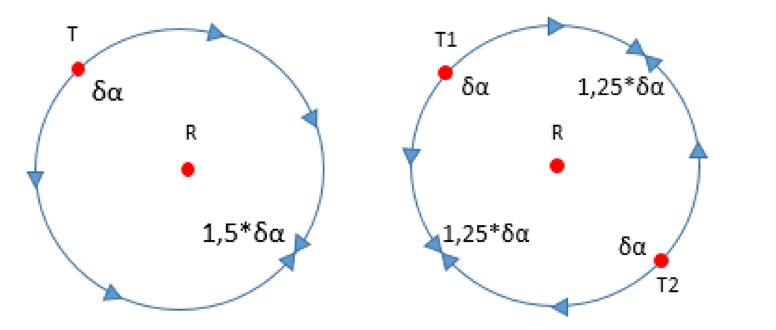

Figure 4: **Variation of $\delta\alpha$ with one and two targets**

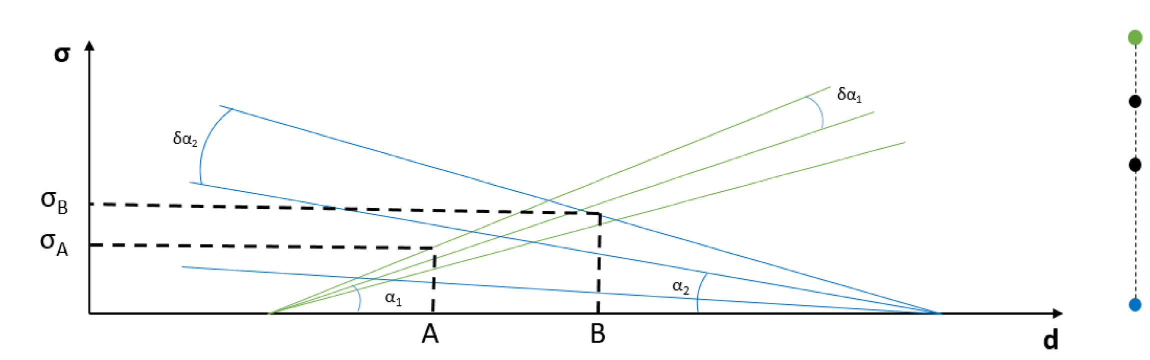

Figure 5: **Depending on the point we do the extrapolation (here A or B), we use the propagation law of different references (here 1 and 2)**

This ensures that we are taking the most accurate of the worst cases. This gives us a map of the site, with the estimated wind modeling uncertainty at each grid point, like we can see it in figure 6.

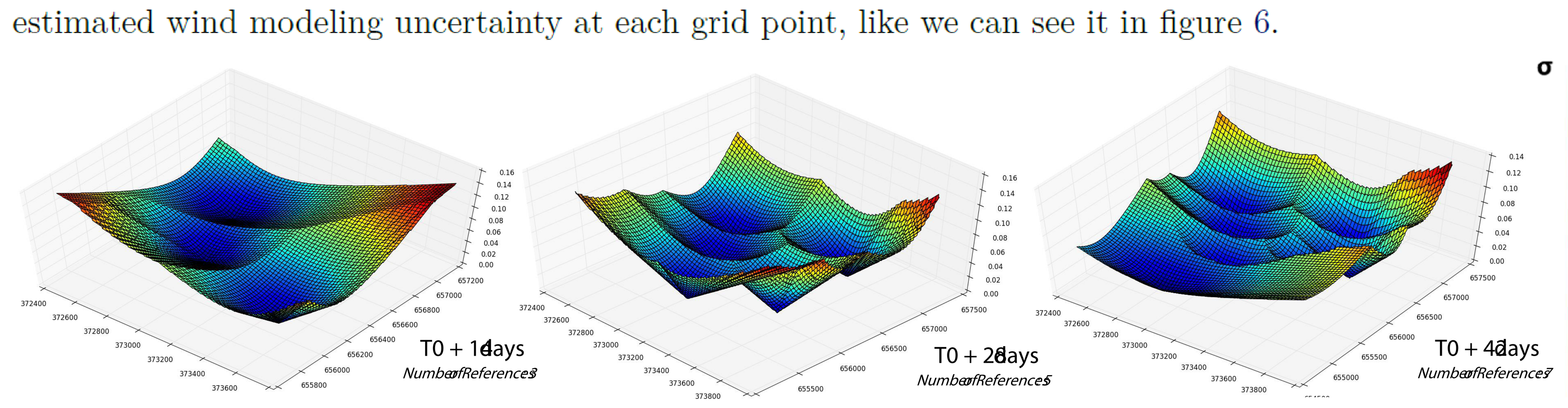

Figure 6: **3D uncertainty map given by our algorithm; the four lower points are the locations of the sensors**

The key of meteoPole's WRA campaigns

As we can see it on the previous map, having more measurement points will reduce the global uncertainty on the wind farm site. Indeed, with more references, the distance to the nearest one for each grid point will be reduced. That's why MeteoPole is encouraging its clients to use moving sensors in addition to the masts, because it allows more measurement points during the same period of time.

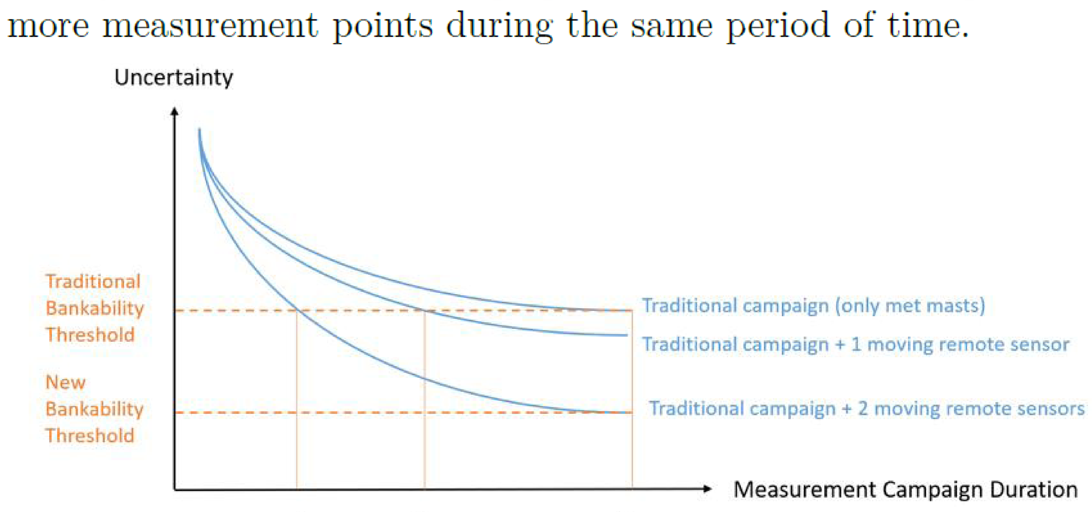

Figure 7: **The use of moving sensors is beneficial for global uncertainty**

One step further: reducing measurement time even for the moving sensors thanks to data of other projects

Once this map is created, the next step is being able to predict the future uncertainty without ending the measurement period, in order to choose to continue measurements or not (moving the groond based LiDAR for example). Indeed, it would be absurd not to use the previous recorded data (at a same ZIX of course).

The idea is, regarding this ZIX, to say how much the uncertainty will statistically decrease if we let the sensor in its place, with a certain probability.

So in our database, we create a different curve for each ZIX, showing the evolution of α versus time. This curve is an average of all the curves registered on the several reference-target couples, with standard deviation at each moment.

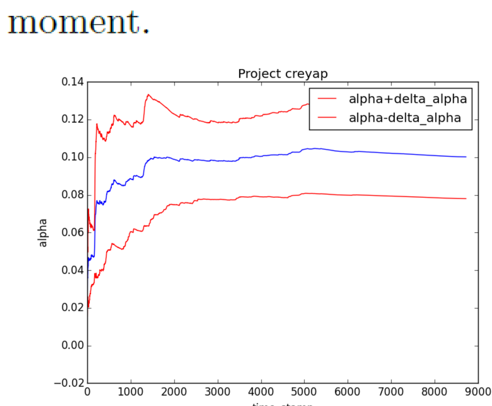

Figure 8: **One example of α versus time, with its standard deviation at each time point**

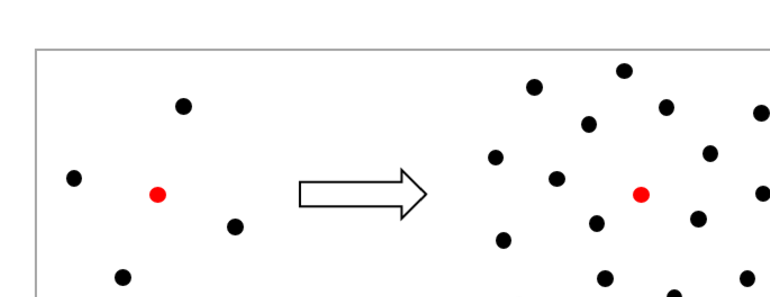

Figure 9: **Possible layouts without and with predicting over 2 months and with one mast (red) and two remote sensors: in the first case the sensors are stationary for one month, in the second for only one week**

In the long run, the idea is to use Machine Learning (and especially Artificial Neural Network) to "predict" the continuation of this $\alpha(t)$ curve, only by studying its shape on the first days/weeks. Indeed, if we can really predict the curve or at least a very late value, it makes the client gain time because thanks to it he can move the Remote Sensor and having another measurement point. This idea is drawn on figure 9.

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