Measure-Correlate-Predict Methods: Case Studies and Software Implementation

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Abstract: The need for an efficient MCP toolbox has now been met by implementation of four different MCP methods into the WindPRO software tool for planning and projecting of wind farms. The four MCP methods vary in complexity, computational requirements and applicability – as such – the analyses herein are supported by two case studies for illustrating these subjects. An outline of the theoretical background of the WindPRO implementation of the MCP methods: Linear Regression, Matrix MCP, Weibull Scale and Wind Index MCP are provided as well as recommendation on where to use the various methods.

Keywords: Measure-Correlate-Predict, MCP, Wind Resources, Wind Turbines, Software Implementation, WindPRO.

1. Introduction and Overview

Various measure-correlate-predict (MCP) methods and algorithms have been studied using wind data from a number of potential wind farm sites. Some of the algorithms and methods have been improved using probabilistic methods, and have then been implemented into the WindPRO software tool for planning and projecting of wind farms. The long term wind data is taken from nearby meteorological stations as well as data from the NCEP/NCAR reanalysis dataset. Below – in Section 2 - is a theoretical outlook of the methods included in WindPRO, followed by two case studies in Section 3.

The MCP module for WindPRO includes the features below, enabling completion of a full MCP analysis within a few hours time:

- Long-term data: NCEP / NCAR data extraction [1]
- Measure: Load of time series data with filtering
- Correlation: Extraction of concurrent data with correlation analysis
- Predict: Linear Regression, Matrix method, Weibull Scale and Wind Index
- STATGEN – generation of wind statistics directly from the MCP result

Overview-reports and detailed reports for each of the methods are available. The global set of NCEP/NCAR long-term reference data is directly available. Data used by the MCP-methods are contained in the WindPRO Meteo objects. The result from the analysis is – typically – a wind statistics generated using WAsP.

2. MCP Models

Below is a brief theoretical overview of the different MCP methods currently implemented in the WindPRO software. This section cover the specific WindPRO implementation of the methods, other authors may have chosen to implement the methods in a different manner.

2.1 Regression

The regression MCP method holds the traditional linear regression MCP analysis as a specialized subset of other regression models using polynomials of other orders. Specializations of the polynomial-fitting methods are also included, provided in order to comply with methods used or suggested by other authors.

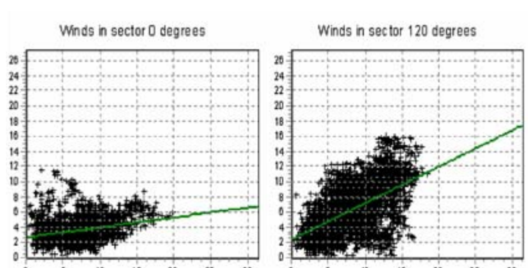


Figure 1: Linear fitting of wind speeds (x: winds at ref. position, y: winds at site position)

One of the specializations is here an MCP method forcing the regression line through the origin (0,0). However, this option should be used only with caution as it typically provides a significantly poorer fit to the data than the methods where a non-zero intersection with the y-axis is allowed.

The regression MCP methods in WindPRO are improved over a traditional linear regression analysis, as a model for the distribution of the residuals is also included. This model allows the regression MCP method to capture the energy content in the MCP corrected site wind distribution much better than regression models without this option. Experience has shown, as much as 10% energy can be erroneously lost in the long-term correction if the model is run without this option. On the other hand, the model may also feed too much energy into the long-term corrected data series, especially if the distribution assumption of the residuals is violated.

2.1.1 Regression Model

Regression modelling, where only one independent (x) and one dependent (Y) variable is present, is based on the following equation:

$$Y = f(x) + e$$

where Y is the dependent variable
x is the independent variable
$f(x)$ is the regression model
e is a random error (residual)

The regression model could be polynomials of any order or other models, but traditionally a linear model is assumed, as this model has been found to give reasonable fits for wind energy estimation. In the case of a regression MCP analysis, the independent variable could be the wind speed measured at the reference position. The dependent variable (Y) is then the wind speed at the local WTG site position.

The following regression models are currently supported in the WindPRO implementation:

Model description	Model eq., f(x)
No model	$Y = x$
Constant	$Y = \beta_0$
Linear - 1st order polynomial	$Y = \beta_1 \cdot x + \beta_0$
Linear regression, though (0,0)	$Y = \beta_1 \cdot x$
2nd order polynomial	$Y = \beta_2 \cdot x^2 + \beta_1 \cdot x + \beta_0$
2nd order polynom. through (0,0)	$Y = \beta_2 \cdot x^2 + \beta_1 \cdot x$

Table 1: Regression Models in WindPRO.

The regression parameters are estimated through a least squares algorithm, utilizing an Amoeba optimization algorithm described in Press et al [5]. The distributions of the random errors may, according to Ross [2], reasonably be assumed to follow a zero mean Gaussian distribution, $e \sim N(0, \sigma)$. However, the distribution of the residuals should be visually checked, so that the assumption is verified as reasonable. This is needed, as the random variable model for the residuals is included in the MCP-modelling in order to give the right energy levels in the new MCP-corrected time series. Please note, that currently the distribution of residuals is conditioned on the reference wind direction only. Thus, conditioned on the reference wind direction, the residuals should be independent on the reference wind speed.

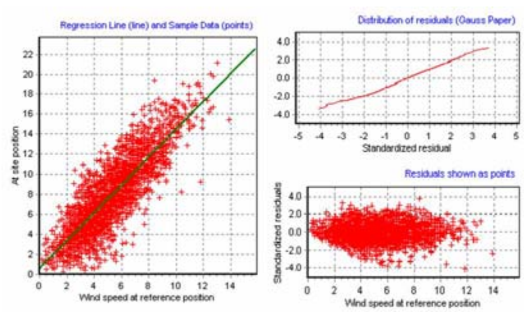


Figure 2: Wind Speed Fit (Left) with the Distribution of the Residuals (plot captured from WindPRO).

2.1.2 Calculating the Long Term Corrected Data

The long term corrected meteorological data is calculated using the regression model (transfer function). All of the samples in the long term reference series are transferred and then the residuals are calculated using a Monte-Carlo simulation technique. The result is a long term corrected wind distribution through an ‘artificial’ time series. For details on Monte-Carlo simulation, see Sørensen [3].

2.2 Weibull Scale

The Weibull Scale method is a very simple empirical method, which does its linear manipulation directly on the Weibull form and scale parameters (*A*,*k*) as well as adjustments on the frequency distribution. The Weibull method has the advantage, that it will match the nature of the wind at most places, but beware that application of this method should be done with caution on locations with significant non-Weibull distributions as well as when the modification of Weibull parameters and frequency needed is very large.

Also, the scaling (which is linear), is a quite simple and radical assumption. A very good directional distribution correlation is needed for the calculation to make sense. The method works best when only small corrections are needed. The Weibull Scale method presumes that the relationship between the Weibull distribution parameters and the frequency follow the general relation:

$$\lambda_{site}^{long} = \left[\lambda_{site}^{short} / \lambda_{reference}^{short}\right] \cdot \lambda_{reference}^{long}$$

where λ is the distribution parameter under consideration (Weibull *A*, *k*)

In the case of considering the frequencies, the modified long-term frequency distribution must be normalized to 100%, i.e. for the *N* sectors under consideration:

$$f_{site,i}^{long} = \frac{\left[\dfrac{f_{site,i}^{short}}{f_{reference,i}^{short}}\right] \cdot f_{reference,i}^{long}}{\sum_{i=1}^{N}\left[\left[\dfrac{f_{site,i}^{short}}{f_{reference,i}^{short}}\right] \cdot f_{reference,i}^{long}\right]}$$

where f is the frequency
N is the number of sectors (typically 12)
i is the sector under consideration

Weibull Scale MCP primarily requires look-up in the appropriate Weibull distributions, calculating the correction table and finally doing the calculation of the long-term distribution.

2.3 Matrix Method

The matrix method in WindPRO models the changes in wind speed (speed-up) and wind direction (wind veer) through joint distributions fitted on the ‘matrix’ of wind speed bins and wind direction bins.

The parallel period of measured wind data is used to calculate the set of non-linear transfer functions, used for transferring wind speeds and wind directions from the reference site to the site position. Since real measurements will suffer from data missing in bins in the dataset, this method needs a way to substitute the missing input bins. In WindPRO, polynomials are fitted to the statistics of the sample data enabling this interpolation/extrapolation. The user may choose to either use polynomials fitted to the data statistics or, where appropriate, to use the measured raw samples directly when doing the matrix MCP.

A basic assumption of the matrix method is that the long-term site data (wind speed and direction) can be expressed through the simultaneous measurements of on-site data and reference site data. Actually this relationship is basically modelled through a joint distribution between the two variables wind speed-up and wind veer. How this joint distribution is modelled should actually depend on the data in question, but experience using the WindPRO MCP, suggests that a combination of binned sample distributions and modelled joint Gaussian distributions seem to work quite well.

The transfer model, given as a conditional distribution, is actually the key distribution in the generalized matrix method. The distribution gives the relationship between the site wind climate and the reference wind climate. When applying the matrix method this conditional distribution is stipulated to hold regardless of the time frame considered.

2.3.1 Matrix MCP Modelling

The Matrix MCP in WindPRO models the wind speed-up and the wind veer as functions of the wind speed and wind direction on the reference site, see Figure 3 and Figure 4. Two modelling options are available in WindPRO, either to use the measured samples themselves (through a bootstrap re-sampling technique) or alternatively to use the fitted polynomial model (actually through a joint Gaussian random variable). If no (or only a few) sample data is available in a particular bin, then the polynomial model is always used.

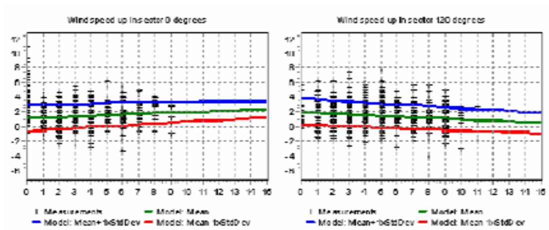


Figure 3: Sample data and first order model for the wind speed-up (x: wind at reference, y=speed-up).

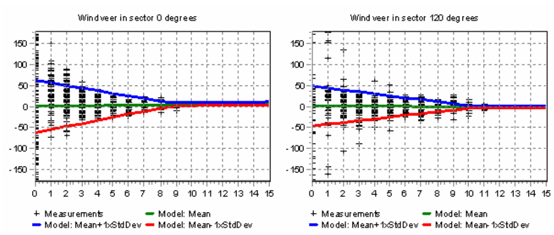


Figure 4: Sample data and first order model for the wind veer (x: wind at reference, y=wind veer).

The model is based on the joint distribution of the measured wind speed-ups and wind veers. Thus, for each measured sample it is necessary to calculate/measure pairs of the two quantities (a pair is data with identical timestamps):

$$\Delta u = u_{site} - u_{reference}$$

$$\Delta \theta = \theta_{site} - \theta_{reference}$$

where Δu is the wind speed-up
u_{site} the wind speed at the site position
$u_{reference}$ the wind speed at the reference site
$\Delta\theta$ is the wind veer
θ_{site} the wind veer at the site position
$\theta_{reference}$ the wind veer at the reference site

The joint distribution of $f_{\Delta u, \Delta\theta}$ is then modelled conditioned on the wind speed and the wind direction on the reference site. These joint distributions are represented as either through the samples (bootstrap model) or through a joint Gaussian distribution, see Figure 5. In the case of the joint Gaussian distribution, the distribution parameters – mean, standard deviation and correlation - are modelled through polynomials of any (user defined) order.

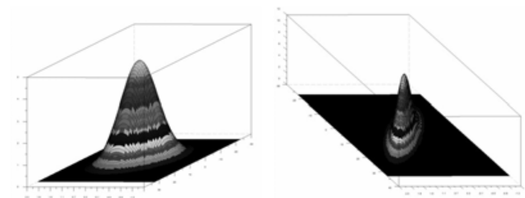


Figure 5: Bivariate Gaussian Distribution: Example of the Joint Speed-Up and Wind Veer Distribution.

2.3.2 Data, Distributions and Statistical Moments

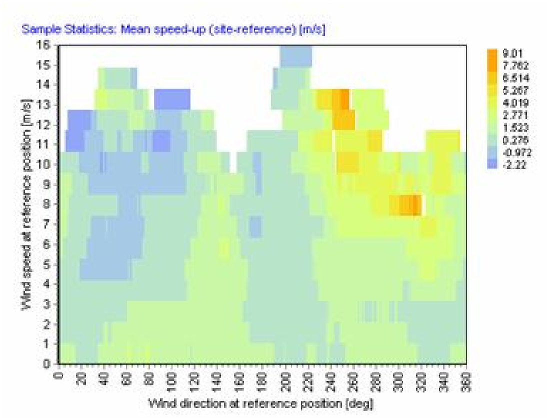
When the data has been measured and a match between the short-term site data and the short-term reference data has been established, then the samples are sorted into bins with the resolution 1 m/s and 1 degree. Since a 1-degree angular resolution is too small in most cases, it is possible to feed in data from a larger window, typically pre-set to around 30 degrees. The result from this binning is a set of joint sample distributions of wind veer and wind speed-up. Since the data is binned with wind speed and wind direction, these sample distributions are said to be conditioned on the mean wind speed at the reference position and the wind direction on the reference position. The calculated distributions are used directly in a bootstrapping technique (see Efron & Tibshirani [4]) when doing the Matrix MCP calculation.

Based on the sample distributions, the following sample statistics are calculated for the wind veer and the wind speed:

- Mean value
- Standard deviation
- Skewness
- Kurtosis
- Correlation

2.3.3 Polynomial Model of Statistical Moments

In order to enable interpolations and extrapolations into bins where no data is present, we choose to parameterize a model fitted to the sample distribution statistics. This parametric distribution is represented by the two first statistical moments and the correlation, and it is assumed that a joint Gaussian distribution is a reasonable distribution assumption. Note, that even if the Gaussian distribution assumption may seem a bit crude, then – in most cases, the parametric model will only be applied in cases where limited or no sample data is available. Thus, the influence of this assumption is limited, as most long-term corrected samples are typically based on the re-sampling approach.



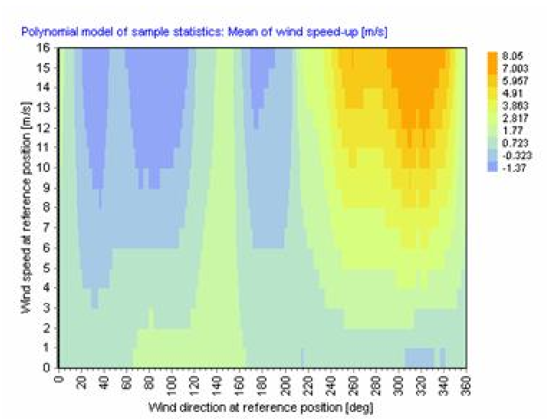


Figure 6: Sample Statistics (Top) and Polynomial Model (Bottom). Here a model of the mean speed-up.

The mean, standard deviation and correlation are now modelled as 'slices' of polynomial surfaces:

$$P\,|\,(U_{reference},\theta_{reference}) = \sum_{i=0}^{n} a_i(\theta_{reference})\,U_{reference}{}^{i}$$

where P denotes the sample statistical moment (or correlation) considered
n is the order of the polynomial
a_i is the polynomial coefficients (which are also functions of $\theta_{reference}$)

An example of this modelling is shown in Figure 6 (bottom). where the surface model seems to capture the trends in the sample data quite well (bottom of Figure 6). In this case 1-st order polynomials are used in all cases except for the mean wind veer where a 0-th order polynomial is used. Note, that the user may choose a polynomial of any order, if this fits the data more accurately.

2.3.4 Calculating the Long Term Corrected Data

As (partly) in the case of regression MCP (see Section 2.1), the long-term corrected meteorological data is calculated using Bootstrap and Monte-Carlo simulation techniques, i.e. probabilistic methods enabling generation of the long-term corrected wind distribution through an 'artificial' time series. Again, for details on the Monte-Carlo simulation, see Sørensen [3], for an introduction to the Bootstrap, see Efron et al [4].

2.4 Wind Index MCP

The index correlation method is a method creating the MCP analysis by means of monthly averages of the energy yield, thus disregarding the directional distribution of the winds. Even though this method may seem rather crude and primitive when comparing to other more advanced MCP methods, which takes the wind veer into account; this method has its advantages in stability and performance as it may even succeed in the cases where other MCP methods seem to fail. This is due to the fact, that the wind indexes are related directly to WTG energy yield and that the method allows the production calculation to be completed using actual measured data before applying the correction.

The Wind Index MCP method in WindPRO offers the opportunity to calculate the wind indexes using real power curves from the wind turbines included in the wind turbine catalogue in WindPRO. Also a generic power curve based on a truncated squared wind speed approach may be chosen. When the wind indexes are calculated, the MCP correction is done on the estimated WTG energy yield, i.e. by multiplying the production estimated with a correction factor based on the difference in the wind index from the short-term site data to the long-term site data estimate.

2.4.1 WTG Power Curve in Wind Index MCP

The energy level in the wind is proportional to the third power of the wind speed. However, since the power curve of a WTG is a non-linear function of the wind speed the wind index is typically modelled as either

1. Through a generic power curve, e.g. the square of the wind speed for wind below the stall onset and a constant above the stall onset:

$$P(u) = \begin{cases} u^2 & \text{for } u < u_{stall} \\ u_{stall}{}^2 & \text{for } u \geq u_{stall} \end{cases}$$

2. From a real power curve, *P(u)*, see an example from a Vestas V44 in the Figure 7.

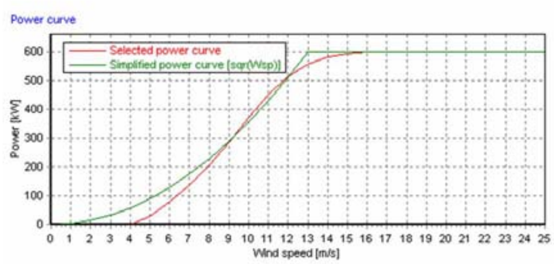


Figure 7: Power Curve from Vestas V44 and Simple Power Curve (scaled to fit the maximum power of the Vestas WTG).

2.4.2 Calculating the Wind Index

The average power output, W, is calculated using the modelled or measured power curve, $P(u)$:

$$W = \sum_{i=1}^{N} P(u_i) \Big/ N$$

where N is the number of measured wind speeds within the period considered
u_i is the i-th wind speed measurement (typically 10 minute mean wind speeds)

In order for the power output (calculated for site and reference) to be comparable they must be based on a similar mean wind speed. This is done by assuming a sector uniform shear that can be applied so that both concurrent mean wind speeds are set to a fixed user-inferred wind speed, typically the expected mean wind speed at hub height. The individual wind speed measurements are thus multiplied with the relevant factor.

Both full time series wind speeds will be adjusted with the same ratio as the one applied to the respective concurrent time series. The argument for this operation is that the variations in wind speed will only be interpreted correctly in terms of wind energy if a comparable section of the power curve is considered.

In WindPRO Wind Index MCP four different average power outputs are calculated. These are: the full reference W_{Rf}, the concurrent reference W_{Rc}, the concurrent site W_{Sc}, and the full site W_{Sf}. Please note that in this method the entire measured site data set is retained with original frequency and period length. The power output for the full reference, W_{Rf}, is set to index =100 (unless specifically stated otherwise) and the ratio in power output between W_{Rf} and W_{Rc} then gives the index of the concurrent period so that

$$I_{Rf} = 100$$

$$I_{Rc} = \frac{W_{Rc} \cdot 100}{W_{Rf}}$$

where I is the wind index of the relevant period.

The assumption is now that the index for the concurrent period at the reference is the same as the index for the concurrent period at the site. That this is the case needs to be tested through a correlation analysis.

$$I_{Sc} = I_{Rc}$$

Knowing the index of the concurrent period on the site means that it is possible to find the index for the entire site measurement period, including the original frequency of measurements. The result is the wind index for the measurement period, which is given by

$$I_{Sf} = \frac{W_{Sf} \cdot I_{Sc}}{W_{Sc}}$$

2.4.3 Wind Index Correlation

In order to make the crucial assumption that the wind index for the concurrent period of the reference is identical to the index of the concurrent period of the site it is necessary to establish whether there is correlation between the two data sets. This can be established using the monthly wind index.

Wind indexes are calculated for each month during the concurrent period comparing the monthly average power output to that of the entire concurrent period. This is done for both reference and site data.

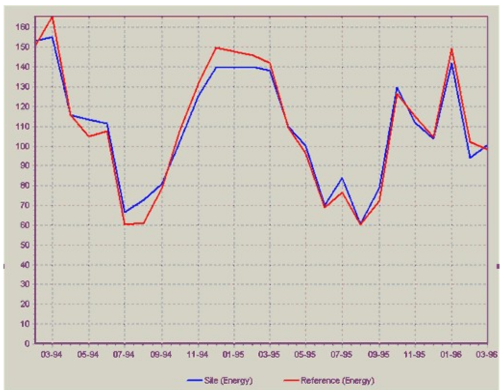


Figure 8: Monthly Wind Index for Reference and Concurrent Data.

When the monthly wind indexes are plotted against each other like shown in Figure 8 the course of the indexes must be similar. If they are divergent it is a sign that the climate at the two locations is different and the assumption of similar index for the same period may fail. Similarly does the assumption that the reference data are representative for long-term conditions at the site. The correlation is measured in either correlation value of the monthly indexes or as a standard error of the difference between the index graphs.

2.4.4 Wind Index Correction

When the wind index for measured site data has been found, it is converted to a correction factor

$$C_{Sf} = \frac{100}{I_{Sf}}$$

where C_{Sf} is the correction factor to the full site data

This correction factor needs to be applied to the final result of the energy calculation. If a wind statistic is created in relation to the long term correction calculation the correction factor is automatically embedded in the resulting windstatistic and will be applied whenever the windstatistic is used. The term used for the correction factor in WindPRO is the Regional Correction Factor (RCF).

3. Case Studies

In this paper we consider two sites: one in Ireland and one in Denmark. Both sites are evaluated using long term data from ground stations and from NCEP/NCAR reanalysis data [1].

In these analysis' we focus the presentation on aggregated results only. However most of the methods allow a very detailed analysis of results, were the long term distributions are compared directly versus the measured joint distribution of wind speed and wind directions.

3.1 Doing the Comparison: Using a WTG Index

In order to do realistic calculations and to draw conclusions about model performance, we use a so-called wind turbine generator index (WTG index) to compare models. This index is chosen, as it reflects the wind energy potential at the site, as seen from a WTG point-of-view. The index is often used in the WindPRO software [7] to compare different WTG performances through the energy levels found in the calculated wind statistics. It is calculated from the wind statistic using a generic power curve with a roughness class 1 position and a 50 meter hub height. The WTG index level is relative (in percent) to 1025 kWh/(m^2 year).

The wind statistics are actually calculated using the WindPRO / STATGEN feature which executes a WAsP [6] calculation. An execution thus requires a digital terrain model as well as a full roughness classification of the site. Also a meteorological mast position and height is needed for the local site data, which the NCEP/NCAR data lacks, disqualifying this dataset for a direct WTG Index analysis as local data. However, as reference data, the NCEP/NCAR data is a very valuable source.

3.2 Case: Cronalaght, Ireland

This site is situated in Donegal, Ireland at about N 55.1º W 8.2º. Five Vestas V39 600 kW turbines were erected in a phase one development, later – in year 2000, three

V47 660 kW were added. The Vestas V39 turbines hold more than 5 years of production data and this data were adjusted to reflect the long term climate for the site.

An overview of the site is shown in Figure 9 and Figure 10. Note the meteorological mast is situated about 1800 meters to the west of the site.

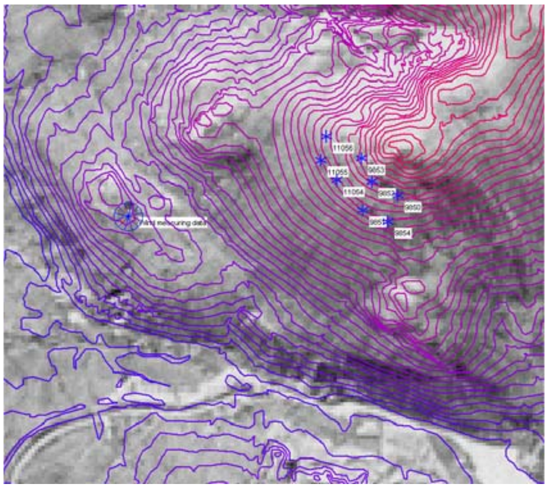


Figure 9: Part of Digital Height Model and WTGs.

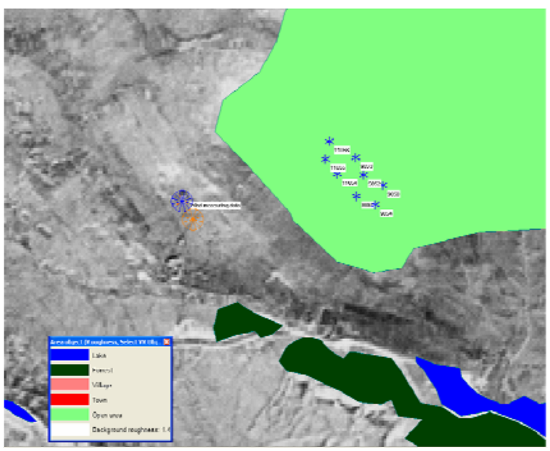


Figure 10: Part of Roughness Classification and WTGs.

For energy yield analysis we have the following wind data available:

Source	Period	WTG Energy
Local mast – 30 m	1994-1996	164.6%
NCEP/NCAR	1990-2007	N/A
Regional mast	1973-1979	143.8%
Regional mast	1991-2004	N/A

Table 2:Cronalaght Case: Data Sources.

3.2.1: Analysis Utilizing WTG Production Data

Doing a WAsP calculation using the local meteorological mast data and comparing with the measured production figures, shows that the measured production is only about 89% to 93% of what is calculated when using the local data. This means, that the 'WTG Energy Level' actually should be in the range from 146.5% to 153.1% instead of the 164.6% in the Table 2. This significant over-estimation of the calculated production could be caused by long-term effects. First, when doing the MCP analysis, it is very important visually to check the correlation between site and regional data, see Figure 11. This figure shows average monthly wind speeds of 1 year concurrent period. The correlation seems very fine, allowing us to continue the analysis.

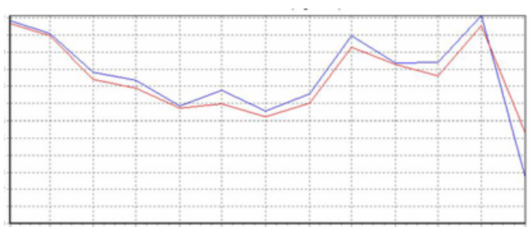


Figure 11: Correlation (monthly wind speed averages): Local Data (blue) vs. NCAR data (red)

Doing the four different MCP methods utilizing both the full 14 years of Malin Head time series data and the 17 years of NCAR data , this yield the results as shown in Table 3.

MCP Method	WTG Energy	
	Malin	NCAR
Linear	152.9%	152.2%
Matrix MCP	152.4%	151.4%
Weibull Scale	152.4%	153.1%
Wind Index Method	150.1%	152.4%

Table 3: MCP Corrected Local Data using Malin Head and NCEP / NCAR Data.

The results seem very reassuring; all methods succeed in giving results within the very tight limit that the production analysis provided us (147%-153%).

3.2.2 Slicing Analysis – Model Performance

An additional analysis option is to test the MCP methods versus a known result – a so-called self prediction. We here choose to 'slice' one year of data from the local measurements and to slice the 3 years of concurrent data (1994-1996) from the regional mast and the NCEP/NCAR data. In that respect, our 'long term reference goal' is actually the 164.6% WTG energy level that was measured. The measured local wind speed in 30 m height in the 3 year period was 9.4 m/s. Now, applying different MCP methods and adjusting some of the different options available in the methods yield the results shown in Table 4 and Table 5.

MCP Method	Wind Speed	WTG Energy
Linear – no resampling	9.31 m/s	163.8%
Linear – residual resampling	9.50 m/s	167.5%
Linear – no resamp. – 1 sector	9.23 m/s	162.0%
Matrix	9.23 m/s	160.4%
Weibull Scale	9.30 m/s	162.4%
Wind Index Method	N/A	160.4%

Table 4: MCP Corrected Local Data using Regional Ground Data (Malin Head).

Using the regional ground data in the MCP analysis, Table 4, yields an average WTG energy yield equal to 162.8%, which is only 1.1% from the local measured level in Table 2. The standard deviation of the WTG indexes is 2.7%.

MCP Method	Wind Speed	WTG Energy
Linear – no resampling	9.46 m/s	166.9%
Linear – residual resampling	9.56 m/s	169.0%
Linear – no resam. – 1 sector	9.44 m/s	165.8%
Matrix	9.34 m/s	163.3%
Weibull Scale	9.44 m/s	165.5%
Wind Index Method	N/A	163.7%

Table 5: MCP Corrected Local Data using NCEP / NCAR Data.

The NCEP / NCAR data in the MCP analysis yields an average WTG energy level of 165.7% which is within 0.7% of what is measured. In this case, it seems, that the NCEP / NCAR data works really fine on this site. The standard deviation is 2.1%.

3.3 Case Alsted / Risø, Denmark

Two meteorological masts at Alstedgårde and Risø on Zealand, Denmark are used to test the various MCP methods. We choose to slice one year of data from the 44 m height on the Risø mast and then to use the 10 meter data from Alstedgårde as long term reference data. Also the NCEP / NCAR data is tested as the long-term data.

Source	Period	WTG Energy
Alsted mast – 10 m	1996-1998	108.6%
Alsted mast – 10 m	1996	103.8%
Risø mast – 44 m	1996-1998	83.8%
Risø mast – 44 m	1996	76.7%
NCEP / NCAR	1987-2007	N/A

Table 6: Alstedgårde/Risø Case: Data Sources.

In Table 6, it is seen – for the same period considered – that the Risø mast holds a significant lower energy level than the Alsted position.

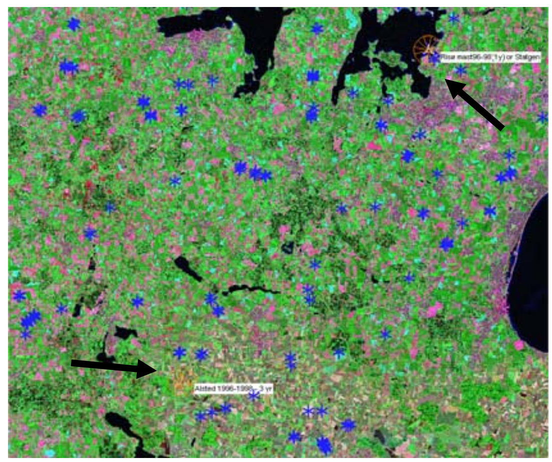


Figure 12: Part of Central Zealand, Denmark. Blue markers denote existing WTG. Arrows show the masts.

3.3.1 Predicting the Risø Mast using Alsted Data

The measured 3 year level to be used in the validation is the 83.8% WTG Index level as shown in Table 6. The corresponding measured wind speed is 6.24 m/s The 'sliced´' year has a level of 76.7%, so we would expect that all MCP long term corrections yields an increase in the energy level. Below – in Table 7 – the results using the Alsted mast as long-term reference.

MCP Method	Wind Speed	WTG Energy
Linear – no resampling	6.08 m/s	79.0%
Linear – residual resampling	6.23 m/s	83.7%
Regression – 2nd order poly.	6.23 m/s	83.6%
Matrix - resampling	6.14 m/s	81.2%
Matrix – polynominal model	6.31 m/s	85.7%
Weibull Scale	6.09 m/s	79.5%
Wind Index Method	N/A	79.7%

Table 7: Risø 44m data corrected using Alsted Data.

As shown in the Table 7, the models perform as expected all increasing the WTG energy levels. The average WTG Index is 81.8% which is 1% lower than what is measured on the site. The coefficient of variation is 3.1%, showing that not all models perform equally well - even if the trend is correct for all methods.

3.3.2 Predicting the Risø Mast using NCAR Data

MCP Method	Wind Speed	WTG Energy
Linear – no resampling	6.12 m/s	80.5%
Linear – residual resampling	6.24 m/s	84.8%
Matrix	5.98 m/s	76.4%
Weibull Scale	6.06 m/s	78.5%
Wind Index Method	N/A	81.9%

Table 8: Risø 44 m data Corrected using NCAR Data.

When comparing the Table 8 with the 83.8% long term level in Table 6, then it is obvious that the Matrix Method and Weibull Scale method fails. This is due to the very sparse long-term reference data set, with only one sample per 6 hours. It is our experience that the Wind Index method is much more robust when applying such datasets.

4. Conclusion and Recommendations

The current paper outlines the implemented MCP methods in WindPRO. For additional details on the implemented methods and alternative MCP methods we refer to the WindPRO manual [7] and the references [8]-[11].

The WindPRO MCP methods offer an easy access to a range of MCP methods and a valuable toolbox, which again provides an easy, fast and accurate analysis within a few hours time.

As indicated in the above case studies, in general all models show the right trends when modifying the local data into a modelled long term representative dataset. However not all models perform equally well in all situations. Based on our experience applying the models to a wide range of sites, we suggest using the regression model and the matrix model for sites where both local site data and reference ground data are available as high quality and detailed time series. On sites, where the data is of limited quality and/or the data are available on only sparse intervals (e.g. the 6 hourly NCEP/NCAR data), we suggest using the Wind Index Method.

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