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Report on procedures and code integration on the estimation of expected net energy yield and its associated uncertainty ranges for offshore wind farms and wind farm clusters

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1 EXECUTIVE SUMMARY

This report is complementary to the EERA-DTOC deliverable [D3.1] on the "Procedure for the estimation of the expected net energy yield and its associated uncertainty ranges for offshore wind farms and wind farm clusters".

The deliverable [D3.1] presents a comparative practical analysis of the different methodologies and techniques used in the assessment of the Net Annual Energy Production (AEP_{NET}) for offshore wind farms and the associated uncertainties.

In the present document, a brief theoretical description of the steps, losses, and uncertainties that need to be accounted for the AEP_{NET} calculations is provided.

This report summarizes different points of view and procedures to estimate the AEP_{NET}, and the corresponding losses and uncertainties. Besides, the possibility of integrating these procedures into a general code will be discussed.

2 INTRODUCTION

The Gross Annual Energy Yield (AEP) of a wind farm or cluster is the energy production of the wind farm (cluster) obtained by calculating the predicted free stream hub height wind speed distribution at each turbine location, and the manufacturer's supplied turbine power curve.

In order to calculate the Net Annual Energy Yield (AEP_{NET}) from the Gross Annual Energy Yield (AEP), it is necessary to take into account different losses that must be applied to the initial gross value.

Every wind resource assessment is an uncertain process. Besides, the determination of the power curve and power production of a wind turbine is also potentially subject to error, which causes uncertainty. Furthermore, the loss factors calculation is an uncertainty process (processes). All these different sources of uncertainties must be accounted for calculating the overall AEP_{NET} uncertainty.

An accurate estimation of the expected Net Energy Yield (AEP_{NET}) is essential for possible investors in a wind energy project (wind farm or cluster). It is not only important for investors to choose the best potential high AEP_{NET} projects, but also the ones with the less uncertainty in the final value. Consultant and financial Institutions agree that lowering uncertainty surrounding a proposed wind farm (or cluster) makes the lenders agreeable to better terms. Besides, reductions in uncertainty results in increase in the net present value (NPV)[1] and the internal rate of return (IRR)[2] [1].

Everything just described above evidence the need for an agreement on the procedures for the losses and uncertainties calculation in the AEP_{NET} estimation process, that avoid the fact that different consultants can give very different figures for the same location.

Before starting to work in the EERA-DTOC Work package 3, it was expected that an agreement on the calculation methods for the AEP_{NET}, losses and uncertainties, used by the different partners, will be reached, or at least, it would be possible to describe general methods to be applied to any resource assessment. Furthermore, it was expected to count on methods that could be prepared for codification, stating clearly the inputs and outputs to be combined for the integration into the design tool. But far from this, what it has been concluded from the Work Package 3 (see deliverable 3.1) [D3.1] is that each partner applies different methods for the losses and uncertainties calculations, and furthermore, this methods could vary depending on the particular resource assessment case and place, and in most of the cases, are based on their own experience and there is not a fix method with clear inputs and outputs to be integrated in a tool. The relative high discrepancies showed in the deliverable 3.1 [D3.1] evidence this lack of agreement.

Therefore, although the initial idea of this deliverable 3.2 was to describe clearly the procedure, inputs, and outputs for the code integration of the different methods for the steps, losses and uncertainties in the AEP_{NET} calculations, it rather analyses these processes, and looks into the possibility of integrating this methods into a general code.

In order to elaborate the deliverable, a questionnaire on the procedures for losses and uncertainties calculation has been answered by different partners as well as literature on this matter has been reviewed.

[1] NPV is a present-day dollar-figure of costs and revenues over the lifetime of the project adjusted for inflation

[2] IRR is an internal rate of return akin to the interest a bank would pay on an account, that is, the percent return that an investment will provide

The structure of this document is as follows:

Firstly, a brief description of the steps in the Net Annual Energy Yield (AEP_{NET}) calculation process is provided, taking into account the different losses, and analysing the different options for the estimation procedures, as well as the possibility of integration into a general code.

Secondly, a brief description of the different uncertainty sources and their estimation procedures, as well as the corresponding code integration possibility, is provided. All these uncertainties will be combined in order to calculate the overall Net Annual Energy Yield (AEP_{NET}) uncertainty.

Finally, the conclusions and good practices in Net Annual Energy Yield (AEP_{NET}) assessment as well as in the possibility of code integration will be presented.

3 NET ANNUAL ENERGY PRODUCTION ASSESSMENT

In this section, the different steps to calculate the Net Annual Energy Yield (AEP_{NET}) will be analysed, looking into the procedures and possible code integration for each.

The first step to calculate The Gross Annual Energy Yield (AEP) of a wind farm or cluster is a wind resource site assessment. Then, the results will be combined with the wind turbine(s) power curve to get the AEP value. Finally, the different loss factors will be applied to the AEP in order to calculate the AEP_{NET}.

3.1. WIND RESOURCE ASSESSMENT

The wind resource assessment is based on the calculation of standard values, like the mean and maximum wind speed, wind roses, wind speed distribution and Weibull fit, seasonal and daily evolution, turbulence analysis, etc.

Nevertheless, the most important variable for the AEP_{NET} estimation is the wind speed at the hub height level at each one of the wind farm (cluster) turbines location.

The steps for this wind speed estimation are presented below.

3.1.1. Quality Control analysis of the data base

To carry out the wind resource assessment, a reliable database is needed.

Usually, the database is gathered from a meteorological mast placed at the project site. Sometimes, lidar or sodar measurements are also available, but in most of the cases, this measurements don't cover a period long enough for the complete analysis, and they are only used to validate the onsite mast measurements.

Another option, in case of places where there is a lack of measurements (as for example many offshore places, where it is difficult to install meteorological masts), the data base (virtual data in this case) is calculated using different models, with the advantage of not needing further height or long term extrapolation and even being able to account for the wake effects (see deliverables 3.1, 1.3 and 1.4).

At the moment, most of the wind resource assessments are performed by analysing mast data bases, and before this analysis, a *Quality Control* procedure must be applied to the data, in order to ensure the data reliability.

This procedure allows for checking the data, applying different filters for "cleaning" the data series, and eventually (whenever there is another reference data set) "filling" the missing values to complete the series.

This filtering process is very important and must be performed by experts, because the criteria used for the different sites could be different (depending on the climate characteristics and mesoscale wind conditions).

Both from the literature and the partners answers to the questionnaire, the conclusion is that there are not general rules for filtering criteria, and this fact can lead to different results in the following analysis, and furthermore, can be an important error source.

For instance, the measures with standard deviation zero, or mean speed greater than maximum speed, etc. should be eliminated. Other criteria are based in establishing possible ranges for the different variables, depending on the site to be analysed. But there are cases in which, for instance 3 or 4 consecutive equal values are considered wrong when they are right values. Another example of wrong filtering is to discard the top anemometer value when it is not the expected value according to the lower anemometers, without taking into account the mast shadow, or considering wrong values those in which the wind speed at high levels is lower than the wind speed at the lower levels.

An illustrative example of a more complex process for filtering and data correction is provided by A. Westerhellweg, et all [2] proposing a method for the Fino1 mast correction, based on the vanishing vertical wind gradients during very unstable situations, enabling a "uniform ambient flow mast correction" (UAM).

The above comments and the differences between the different partners filtering methods showed in the deliverable 3.1 [D3.1], evidence the need for an agreement on the filtering criteria rules, and at the same time, the difficulty of establishing general criteria to be applied everywhere.

Regarding the possibility of integrating the filtering process into the code, as an automatic process, all the partners think that it is possible, but only for the most simple and clear rules, and in any case, the software should be handled by an expert, in order to give the appropriate inputs, taking into account the specific climatological characteristics of the place and checking the process.

3.1.2. Wind speed distribution and Weibull Parameters Estimation

The estimation of the wind speed distribution is the base to calculate the AEP.

If there is a data base long enough (as it is the case of Fino 1, used for the test case in the deliverable 3.1 [D3.1]) this distribution could be estimated from the data base itself and there is no need for fitting to any theoretical distribution.

But the reality is that, unfortunately, in most of the cases, the available data period is much shorter and it very often has missing values.

Therefore, it is usual to fit the real distribution to a theoretical one.

There are different options to choose the optimal model for the wind distribution. Morgan et al. [3] analyse different distributions (as Weibull, Rayleigh, Normal, Gamma, Pearson, Kappa, Wakeby, etc.), concluding that the best option depends on the particular database itself (because of the particular meteorological and site conditions).

Nevertheless, the Weibull distribution is the most commonly used to model wind speed distribution, and it often provides a good approximation to the real one. It relies on two parameters: the scale factor *c* and the shape factor *k*. The Weibull probability density function is shown in Eq. (1).

$$p(U) = (k/c)(U/c)^{k-1} exp(-(U/c)^k) \qquad (1)$$

where *U* is the wind speed.

A statistical model approximation to the wind speed distribution, as opposed to simply using the measured time series or the frequency distribution of the measured data, is

useful for several reasons. The most important is that a statistical model allows for the quality of the wind resource to be quantified by the parameters of the model. In the case of the Weibull distribution, the quality of the wind resource is easily summarized by the values of *c* and *k*.
Besides, there is a relationship between the scale factor c and the mean wind speed, as it is shown in Eq. (2)

$$c = \overline{U}/\Gamma(1 + 1/k) \qquad (2)$$

There are different methods for the Weibull parameters estimation [4] although the most commonly used are the Maximum likelihood method and the empirical one.

Regarding the possibility of integration in a code, it seems relatively easy to integrate the Weibull parameters estimation into a code, and in fact, there are already many software tools for these calculations. Nevertheless, if the nonlinear fit to empirical histogram is employed, as it tends to be non-robust, and to depend on the selection of the initial values, some plausibility check should be integrated (e.g. visual inspection of the result).

Finally, it is important to remark that all the partners agree that the Weibull adjustment must be performed by sectors.

3.1.3. Long term Extrapolation

As the measurements data base usually covers a period not long enough to be representative of the climate values at the site (it is supposed that the minimum period that will cover the wind farm life and could be consider as representative is 20 years), the onsite measurements data base should be validated and extrapolated by using a longer and reliable data base coming either from a mast, lidar or sodar, near the specific site, or from virtual data (outputs from numerical models like MERRA, HIRLAM, ERA Interim, NCEP/NCAR, etc.)

Especially when dealing with offshore places, there is a lack of good quality measurements, both on-site for the particular project and reference data sets.

The Measure-Correlate-Predict (MCP) Method [5] is a statistical technique used for predicting the long term wind resource at proposed wind farm site by relating measurements from an on-site short-term measurement campaign to the long term reference data series..

The differences in the reference data base and the methodology used to fit the measurements to the reference base, can lead to very different results when the modelled data base is employed for further calculations (e.g. AEP), as it is showed in the Deliverable 3.1 [D3.1] test case.

In applying MCP, careful attention must be paid to the temporal period employed and how well it represents the primary meteorological scales responsible for the climatological relationship [6]. For example, if the reference data base contains 1 data every 6 hours, there are some lower scale phenomena that are avoided.

Taylor et al. [6] analyse three different methods, based not only on different procedures (in some cases directional ratios are employed instead of directional regressions) but also in the reference data set scale. They conclude that depending on the particular case, one method performs better than the others, but it can't be generalized there is a best option for every case.

In any case, they [6] conclude that it is necessary to fit at least a full year data, in order to care for the seasonal changes. Nevertheless, applying the same MCP technique at the same place, using periods of different lengths, the results can be very different.

Lybech Thøgersen et al. [7] analyse four different MCP methods into the WIndPRO [8] software tool for planning and projecting of wind farms.

In the EERA-DTOC Deliverable 3.1 [D3.1], CENER proposes seven possible algorithms for the fitting, regarding the long term estimation.

It can be concluded that the long term estimation is a very important process in which the different methods applied can lead to very different results, and can greatly affect the AEP estimation. Therefore, careful attention must be paid to this process.

Of course, the different mathematical processes can be integrated in a code, but it is difficult to choose the best option, so that the code could ask for different expert inputs, in order to choose the most appropriate algorithm for each case.

3.1.4. Hub height extrapolation

The estimation of the AEP is based on the hub height wind speed values at every wind turbine.

The measurement heights of meteorological towers (met towers) are typically significantly lower than turbine hub heights, especially in the case of the large offshore wind turbines. That is why a shear model is generally needed to extrapolate the measured wind resource at the lower measurement height, to the turbine hub height.

There are different methods for the wind speed profile estimation.

The most simple and commonly used method is the potential law that expresses the relationship between the two level wind speeds (U_1 and U_2), depending on the power ratio between the these level heights (Z_1 and Z_2)

$$\frac{U_2}{U_1} = \left(\frac{z_2}{z_1}\right)^{\alpha} \tag{3}$$

Where α is usually called shear exponent, power law coefficient, or simply 'alpha'.

$$\alpha = ln(\bar{U}_{M2}/\bar{U}_{M1})/ln(h_2/h_1) \tag{4}$$

The predicted mean wind speed, $\bar{U}_{HUB}$, at height h_3 can then be calculated using Eq. (5).

$$\overline{U}_{HUB} = \overline{U}_{M2}(h_3/h_2)^{\ln(\sigma_{M2}/\sigma_{M1})/\ln(h_2/h_1)} \quad (5)$$

In the literature, the wind shear coefficient is generally approximated between 0.14 and 0,20. However, in real situations, this coefficient is not constant and depends on different factors, as the temperature, meteorological lapse rate, atmospheric stability, pressure, humidity, daily evolution, season, mean wind speed, direction and surface roughness.

As the effect of these factors influences the wind velocity data, it is also expected to be reflected in the wind shear exponent. But the reality is that in many cases, this formula is too simple to account for all these factors affecting the wind speed profile.

Therefore, other alternative formulas are employed for determine the wind speed profile:

A more sophisticated alternative is given by Zekai Sen et al. [9], who propose an “Extended power law”, in which, on the contrary to the classical approach (eq.3), not only the means of wind speeds are at different levels, but also their standard deviations and cross-correlation coefficient, are taken into account. In practice, most often, the cross-correlation coefficient between different levels wind speed is overlooked by assuming that there are no random fluctuations around the mean speed values, which brings the implication that the standard deviations are equal to zero. But these assumptions are not valid, because in actual weather, there are always fluctuations in the wind speed records.

Another option is to apply the Monin-Obukhov theory. In this case, the wind profile can be estimated using the two parameters: Monin-Obukhov length (L) and sea surface roughness (z_0):

$$U(z) = \frac{u_f}{K}\left[\ln\frac{z}{z_0} - \Psi\left(\frac{z}{L}\right)\right] \quad (6)$$

Where U is the wind speed, z is the height above ground level, u_* is the friction velocity, K is the von Karman constant (normally assumed as 0.4), Ψ(z/L) is the stability function, L is a scale factor called the Monin-Obukhov length, and z_0 is the surface roughness coefficient, whose length is expressed in meters and depends basically on the land type, spacing and height of the roughness factor (water, grass, etc.) and it ranges from 0.0002 up to 1.6 or more.

This equation is strictly valid only for quasi-steady conditions in the surface layer although it can also provide good predictions of ensemble-averaged atmospheric boundary layer profiles in sites with predominant unstable-neutral conditions.

For the especial case of neutral stability, the Monin- Obukhov formula turns into the logarithmic wind profile law

$$U(z) = \frac{u_f}{K}\ln\frac{z}{z_0} \quad (7)$$

Nevertheless, the high probability of occurrences of non-neutral stability situations and the impact of the stability on the wind profile, increases the need for considering the atmospheric stability for the wind speed extrapolation, that can be evaluated using different methods (e.g. covariance, bulk, gradient) [10].

Tambke et al [11] care about the special meteorological characteristics of offshore places marine boundary layer, which must be considered to predict the correct wind speed at the hub height of the wind turbines. The main differences for the marine boundary layer with respect to the land are: the non-linear wind-wave interaction causes a variable, but low surface roughness; the large heat capacity of the water changes the spatio-temporal characteristics of the thermal stratification; and internal boundary layers due to the land-sea discontinuity modify the atmospheric flow.

For these reasons, a new analytic model for marine wind velocity profiles ICWP (Inertially Coupled Wind Profiles) was developed by coupling the Ekman layer profile of the atmosphere to the wave field via a Monin-Obukhov corrected logarithmic wind profile in between [12].

An alternative option for improving the estimation of the hub height wind resource is the use of ground-based remote sensing devices (Lidar or Sodar), which are capable of producing substantial improvements in the accuracy and uncertainty of shear extrapolation predictions [13]. Besides, they have two major advantages: their portability and their ability to measure directly at the wind turbine hub height.

As well as for the long term extrapolation, if the wind resource assessment is based on “virtual data”, coming from the outputs of simulation models (e.g. reanalysis data from numerical models), there is no need for this hub height extrapolation, since the model outputs are given for different heights and places. Nevertheless, these models outputs wind profiles are not always as accurate as it could be expected [12].

Regarding the practical applications, there is an agreement between the partners on the most commonly option for the wind profile estimation based on the two level power law. Nevertheless it would be desirable to use as many levels as possible, and to make a sector wise analysis, as well as to account for the atmospheric stability effects.

The methods above described could be integrated into the general code, but depending on the case and site complexity it could be difficult to account for the model inputs, that, once again, should be provided by experts.

3.2. POWER CURVE

A power curve provides a relationship between the inflow wind at the rotor, and the electrical power output of a wind turbine.

Following the standards IEC 61400-12 [14] :

The measured power curve is determined by applying the “method of bins” for the normalized data sets, using 0,5 m/s bins and by calculation of the mean values of the normalized wind speed and normalized power output for each wind speed bin according to the equations (8) y (9):

$$V_i = \frac{1}{N_i}\sum_{j=1}^{N_i} V_{n,i,j} \tag{8}$$

$$P_i = \frac{1}{N_i}\sum_{j=1}^{N_i} P_{n,i,j} \tag{9}$$

where

V_i is the normalized and averaged wind speed in bin i;

$V_{n,i,j}$ is the normalized wind speed of data set j in bin i;

P_i is the normalized and averaged power output in bin i;

$P_{n,i,j}$ is the normalized power output of data set j in bin i;

N_i is the number of 10 min data sets in bin i.

These values should be calculated from an on-site test at each particular place, but it is not usually this way.

The power curve is usually given by the manufacturer and it may be contractually guarantied.

Nevertheless, the wind speed that appears in this formula is not exactly the hub height wind speed calculated as it is explained above, because the turbulence and other phenomena related to the interaction between the wind and the Wind turbine structure modifies the wind speed. The power curve deviations will be analyzed in section 3.4.4.

3.3. ANNUAL GROSS ENERGY (AEP)

Once the wind resource at a site has been determined (i.e., the wind speed at the hub height), it is combined with a selected power curve to yield an estimate of the energy production of the wind turbine (wind farm or cluster).

The Annual Gross Energy (before accounting for losses) can be obtained according to the equation:

$$AEP = \sum_i P(U_i) N_i \tag{10}$$

where $P(U_i)$ is the power output for each wind speed interval i , and N_i the number of hours in a year for each wind speed interval ($N_i = f_i * 8760$, with f_i the frequency of each wind speed interval).

This formula is applied when a long enough wind data base is provided. Otherwise, a theoretical wind speed distribution F (V) is applied.

Thus, the formula for the AEP estimation is

$$AEP = N_h \sum_{i=1}^{N} [F(V_i) - F(V_{i-1})] \left(\frac{P_{i-1} + P_i}{2}\right) \tag{11}$$

where

AEP is the annual energy production;

N_h is the number of hours in one year ≈ 8760;

N is the number of bins;

V_i is the normalized and averaged wind speed in bin i;

P_i is the normalized and averaged power output in bin i.

F (v_i) is the value of the wind speed model distribution in bin i

3.4. ANNUAL NET ENERGY YIELD (AEP_{NET})

Meteorological phenomena can only be predicted to a certain limited degree. As a consequence it is not possible to make an exact forecast of the wind conditions, even if long-term reference data (which can only represent the past) is used. Furthermore, data collection and processing is always affected by errors and inaccuracies, as it is every mathematical or physical model used to describe or predict real procedures. To compensate the inaccuracies in the modelling approach and basic input data, it is advisable to use “factors of safety” to adjust, or discount the final output.

Two blocks determine the factors of safety: losses (that will be analysed in this section) and uncertainties (that will be analysed in section 3.5).

Therefore, in order to estimate the Annual Net Energy Yield (AEP_{NET}), different losses must be subtracted from the Gross Annual Energy Yield (AEP).

Estimation of energy losses is challenging and requires a great amount of observational and modelling experience. Instead, in most cases, standard values are assumed, based on previous consultants’ experience. Nevertheless, an appropriate estimation of the losses should be carried out, in order to avoid the differences in the total amount energy estimation figures given by different consultants, and to increase its accuracy.

There is considered to be six main sources of energy loss for wind farms, each of which may be subdivided into more detailed loss factors:

- Wake effect
- Electrical losses
- Availability losses
- Turbine performance
- Environmental losses
- Curtailments

The main causes and possible calculation methods for these losses are described below.

3.4.1. Wake effect

The wake effect is the aggregated influence on the energy production of the wind farm, which results from the changes in wind speed caused by the impact of the turbines on each other. It is also important to consider wake effects from neighbouring wind farms and the possible impact of wind farms which will be built in the future.

The wake effect corresponds to the extraction of momentum and energy that the wind turbine imposes on the wind flow through their rotational work. These losses are accounting for the energy lost by the wake interaction between two or more turbines.

Within a wind farm, wind turbines extract energy from the wind, which might affect the potential extraction of energy of downstream turbines. This also means that the potential for a wind farm for extracting energy from the wind resources is going to be limited by its own turbine interacting and by the wake effect of neighboring wind farms.

In all the wake losses models available in the EERA-DTOC project (Work package 1), the individual turbines or wind farms, are model directly or indirectly as a sink of momentum and energy (see deliverables 1.3 and 1.4). Wake losses are relatively complicated to model, as the recovery of the wind behind a wind turbine is a combination of turbulence structures of different scales, i.e. the atmospheric scales turbulence, and the wind turbine rotor scales turbulence. While single turbulence scale is solvable with reasonable precision at an affordable cost, solving multiple scale turbulence requires very large computational resources that are not justified by the relatively large variability of result quality they can produce.

The additional challenge of EERA-DTOC is that the domains required to run multiple wind farms is so large that very large atmospheric scales, approaching planetary scales of turbulence start to be needed to faithfully model the impact of one wind farm to another. This requires coupling the wind farm scale wake models with Mesoscale (a.k.a. cluster-scale) wind farm wake models that are able to capture all the relevant scales of physics.

The way it is planned to be done in practice in the EERA-DTOC project is by running a combination of wind farm and cluster scale models:

- First a wind farm scale flow model to generate a meta-model of a wind farm production with limited inputs (reference wind speed and wind direction)
- Then a Mesoscale (cluster scale) flow model is run, using the wind farm scale flow meta-model to account for the meso-scale wind farm effects.
- Finally the local wind resources created by the Mesoscale wind farm can be used as an input to (possibly another) wind farm scale flow model to estimate the net annual energy production of the target wind farm.

3.4.2. Electrical losses

Any cluster of wind farms involves a considerable electrical infrastructure that inherently will produce a certain amount of electrical losses inside each wind farm, between wind farms inside the cluster, and between the cluster and the shoreline.

The procedure for the estimation of these losses can differ considerably from those at onshore sites and must also be estimated as accurately as possible.

There are electrical losses between the low voltage terminals of each of the wind turbines and the wind farm Point of Connection, which is usually located within a wind farm switching station.

The overall electrical efficiency include the electrical losses encountered when the wind farm is operational and which will be manifested as a reduction in the energy measured by an export meter at the point of connection and is based on the long-term average expected production pattern of the wind farm. It is also necessary to consider the power that the wind farm consumes when the wind farm is not operational.

All these considerations regarding the electrical design, availability and losses are addressed in the corresponding EERA-DTOC work package 2 deliverables.

3.4.3. Availability losses

The turbine availability is the percentage of a year (i.e. 8760 hours) when the turbine is able to generate electrical energy while being connected to the grid.

Therefore, the turbine availability loss factor represents, as a percentage, the factor which needs to be applied to the gross energy to account for the loss of energy associated with the amount of time the turbines are unavailable to produce electricity.

Similar factors are needed for the 'Balance of Plant' availability, which relates to the electrical infrastructure of the site and 'Grid Availability', which relates to the availability of the grid over which power can be exported.

Reasons for the non-availability of a wind turbine are various, and include downtimes for regular maintenance and servicing, component failures (including defect sensors), overheating of components, repairs or exchange of components, as well as errors and downtimes of the superior electrical grid.

The turbine availability can be set to a value by taking into account the experience in the operation of wind turbines in the region and skills of local staff, but considerable mistakes can lead to future unexpected economic losses.

The *Turbine Availability Loss* can depend strongly on various factors including the turbine model, maintenance schedules, O&M (Operations and Maintenance) strategy, distance between the wind farm and the O&M base and the wind farm's wind and wave climate.

RES has developed a software tool called SWARM, which estimates the energy-based Turbine Availability loss for a generic 600 MW offshore wind farm for a number of scenarios. The calculated loss encompasses all energy yield losses that result from turbine downtime. This includes time required to obtain replacement parts, travel to the turbines and carry out repairs, downtime due to scheduled servicing and delays caused by bad weather.

SWARM uses Monte Carlo simulations to model the operation and maintenance of a wind farm. It accounts for predicted failure rates, wind and wave conditions, vessel capability and response times, spares holdings and maintenance resources to forecast operational availability. Each simulation is run for a period of 70 years, to produce an annual average Turbine Availability Loss for the wind farm.

The SWARM model has been applied to the test case in the Deliverable 3.1 [D3.1].The inputs used for the SWARM runs conducted for the EERA DTOC project are:

-Turbine Layout and Turbine Model

A generic turbine power curve was used for this work to represent a typical 6 MW offshore wind turbine. This turbine size was chosen as a typical size for offshore projects currently in development

- Site Wave Climate

The time taken to carry out repairs can depend strongly on the wave climate at the site. If large waves are common, this will lead to increased delays and more lost energy as workboats will often be unable to access the wind farm.

- O&M Strategy

Virtual O&M base locations were defined at various distances from the wind farm centre, from 10 km to 150 km. No real port data were used for this study and all tidal restrictions were ignored.

- Location of O&M Base

Reasonable values were assumed for turbine failure rates and maintenance schedules.

Definition of '*Excess turbine availability loss*'

The SWARM software produces an estimate of the overall percentage of energy lost due to turbine downtime. These results will depend strongly on the assumptions of turbine failure rates, response times and amount of spare parts held at the O&M base. In order to remove some of these dependencies, the results presented here have been normalized relative to a base-case result.

The base-case used here has the following properties:

1. O&M base is at the centre of the wind farm
2. Five workboats with no operational restrictions (i.e. no waves)
3. Same layout and turbine type as described above

The base-case availability loss is therefore the loss that would be seen with minimal travel time to the wind farm and with a perfectly calm sea. For real wind farm scenarios, any additional loss caused by increased travel time and/or high waves is referred to in this study as '*Excess Turbine Availability Loss*'.

Anyone wishing to use these results to calculate an absolute Turbine Availability Loss should first define their own base-case availability loss and combine it with the Excess Turbine Availability Loss provided here. The losses should be combined multiplicatively, as follows:

(1-Total Turbine Availability Loss) = (1-Base Case Loss) x (1-Excess Turbine Availability Loss)

The results of the SWARM simulations are heavily dependent on the input data but will be broadly valid for wind farms of different capacities. But using a significantly different turbine model is likely to impact the absolute availability losses derived.

The O&M strategy has the largest impact on availability losses. Likely, the choice of the wind climate scenarios considered may change significantly the results. For example, for sites far offshore it is possible that an offshore O&M base would be constructed, which would significantly reduce the losses due to travel time.

Results show that the Excess Turbine Availability Loss varies between 0.5% and 10.2% depending on the scenario considered.

The results are intended to be used in order to compare different wind farm strategies rather than as absolute energy yield loss factors.

3.4.4. Turbine performance

Generally, the wind turbines power curve is given by the manufacturer. But this power curve may be quite different, depending on the specific site conditions.

Several manufacturers are thus providing power curves which are calculated from the tests results of several measured ones; the performance of these calculated power curves might be contractually guaranteed by the manufacturers.

But a crucial problem of wind turbine performance testing is that there is no possibility to conduct tests in controlled wind conditions. To handle this specific difficulty and to allow for unified performance testing, the international standards IEC 61400-12 [14] has been worked out. It defines measurement and data analysis procedures which lead to a standardized power curve.

The turbulence, air density, and shear characteristics of a site will affect the power curve of a turbine, with the result that a turbine at a specific site could produce either more or less power than the power curve indicates at a given wind speed. The measured power curve specifically corresponds to a site that meets the IEC standards [14], which require a flat site with very low turbulence, so that effects of turbulence and shear across the rotor face are not taken into account, and consequently the mean wind speed averaged over the rotor face is uncertain.

For practical reasons, power curves are typically measured by the manufacturer in an onshore site. Moreover, the standards IEC 61400-12 are restricted to onshore sites. For offshore sites typically reduced shear and turbulence levels are found due to the rather flat sea surface, compared to onshore sites. Therefore a power curve measured offshore will typically show lower power levels than that of an onshore site, even if measured for identical turbine models. It should nevertheless be noted that the overall energy yield gained offshore is generally higher than onshore, due to significantly higher average wind speeds.

In order to calculate the actual mean wind speed averaged over the rotor-face, FORWIND proposes the following method:

An effective wind speed can be defined knowing the wind speeds u_i at various heights z_i. One can split the rotor area A into layers of area A_i for each height z_i. The effective wind speed is then defined as $u_{eff} = (\mathrm{SUM}_i\ A_i/A\ u_i^3)^{1/3}$, such that the power $P_i \sim A_i\ u_i^3$ extracted from each vertical layer A_i is accounted for.

The IEC [14] definition of the vertical profile gives the wind speed at an altitude z_i as $u_i = u_h(z_i/z_h)^{\alpha}$, knowing the wind speed u_h at hub height z_h. Integrating this into the definition of the effective wind speed gives $u_{eff} = \beta(\alpha)u_h$ with $\beta(\alpha) = (SUM_i\ A_i/A\ (z_i/z_h)^{3\alpha})^{1/3}$. The effective wind speed is the wind speed at hub height corrected by a pre-factor β(α) that depends on the vertical shear α. FORWIND thinks that this correction term β(α) has some theoretical sense, although they could not yet test this on real data.

Besides these considerations, another important correction must be applied to the power curve, because it depends on the air density.

Following the the standards IEC 61400-12 [14], the selected data sets shall be normalized to two reference air densities. One shall be the sea level air density, referring to ISO standard atmosphere (1,225 kg/m³). The other shall be the average of the measured air density data at the test site during periods of valid data collection, rounded to the nearest 0,05 kg/m³. No air density normalization to actual average air density is needed when the actual average air density is within 1,225 ± 0,05 kg/m³.

Alternatively, the other normalization may be carried out to a nominal air density pre-defined for the site. The air density may be determined from measured air temperature and air 10_{min} pressure according to the equation:

$$\rho_{10min} = \frac{B_{10min}}{R.T_{10min}} \tag{12}$$

where

ρ_{10min} is the derived 10 min averaged air density;

T_{10min} is de measured absolute air temperature averaged over 10 min;

B_{10min} is the measured air pressure averaged over 10 min;

R is the gas constant 287,05 J/kg x K).

For a stall-regulated wind turbine with constant pitch and constant rotational speed, data normalization shall be applied to the measured power output according to the equation:

$$P_n = P_{10min} \cdot \frac{\rho_0}{\rho_{10min}} \tag{13}$$

where

P_n is the normalized power output:

P_{10min} is the measured power averaged over 10 min;

ρ_0 is the reference air density.

Finally, the turbine performance high wind hysteresis has to be taken into account:

Most wind turbines will shut down when the wind speed exceeds a certain limit. High wind speed shutdown events can cause significant fatigue loading. Therefore, to prevent repeated start up and shut down of the turbine when winds are close to the shutdown threshold, hysteresis is commonly introduced into the turbine control algorithm. Where a detailed description of the wind turbine cut-in and cut-out parameters are available, this is used to estimate the loss of production due to high wind hysteresis, by repeating the analysis using a power curve with a reduced cut-out wind speed.

3.4.5. Environmental losses

In certain conditions, dirt can form on the blades or, over time, the surface of the blade may degrade. Also, ice can build up on a wind turbine. These influences can affect the energy production of a wind farm in the ways described below. Extremes of weather can also affect the energy production of a wind farm; as can the growth or felling of nearby trees.

3.4.6. Curtailments

Some or all of the turbines within a wind farm may need to be shut down to mitigate issues associated with turbine loading, export to the grid, or certain planning conditions.

3.4.7. Overall Energy loss factor

Once all the losses are calculated, the total AEP_{NET} can be estimated from the AEP.

The above described energy loss factors are labeled ELF_{AV}, ELF_{ELE}, ELF_{WAKE}, ELF_{TP}, ELF_{ENV} and ELF_{CUR} . Each energy loss factor is defined as the ratio of the actual energy produced divided by the ideal energy production if there were no losses. Thus, for example, the ELF_{AV} is simply equal to the actual expected energy production of the wind turbine or wind farm, divided by the hypothetical energy production if there was no maintenance of the turbine(s) or down time, whether scheduled or unscheduled.

The total reduction due to the wind turbine or wind farm energy loss is simply the product of all the energy loss factors. Thus, the overall energy loss factor, *ELF*, is shown in Eq. (14).

$$ELF = ELF_{AV} \times ELF_{ELE} \times ELF_{WAKE} \times ELF_{TP} \times ELF_{ENV} \times ELF_{CUR} \qquad (14)$$

Finally, the Net Annual Energy Yield (AEP_{NET}) will be the product of the Gross Energy Yield (AEP) by the overall energy loss factor

$$AEP_{NET} = AEP \times ELF \qquad (15)$$

An illustrative example of the AEP_{NET} estimation is showed in section 5.

4. UNCERTAINTIES ESTIMATION

Uncertainty analysis is an important part of any assessment of the long-term energy production of a wind farm.

The accuracy and precision of the wind resource assessment and *AEP* calculation must be determined when evaluating a potential site. Wind resource assessment is an uncertain process, and a large number of factors, ranging from wind speed measurement errors to the inherent physical variations in the wind, contribute to this uncertainty.

These various individual sources of error must all be accounted for to provide an estimate of the total uncertainty of the wind resource. Furthermore, power curves and energy loss terms are uncertain as well. When the wind resource, the power curve, and the energy losses are combined to estimate the *AEP*, the uncertainties from all these factors contribute to an overall *AEP* uncertainty. This uncertainty is critical in estimating the risk associated to the potential venture.

Although an uncertainty analysis needs to be considered on a site-specific basis, the general process can be described as follows:

- Identify the different inputs to and processes within the analysis;
- Assign an uncertainty to each of these elements, both in terms of the magnitude of the uncertainty and the shape of the distribution;
- Convert each of the uncertainties into common units of energy;
- Combine the various uncertainties to define a total uncertainty for the entire prediction;
- Present uncertainty statistics at requested levels.

Regarding the uncertainty analysis on energy yield estimation, some significant advances have been made during the last years as it is summarized at the IEC-61400-12-1 standards [14], IEA Recommended Practices 11 on Wind Speed Measurement and use of Cup Anemometer [19], as well as at the MEASNET guideline "Evaluation of site specific wind conditions [15].

Nevertheless, a step forward is needed in the uncertainties estimation, for specific sites, and especially for offshore wind farms and clusters.

Before computing the overall uncertainty, several assumptions must be made:

All measurements are subject to errors, whose size is unknown (uncertain). Thus, the term "uncertainty" is used as a measure of the size of the error.

A classification for the uncertainties is given by the IEC-61400-12-1 standards [14], in which two types of uncertainties are considered: Category A, if the magnitude can be deduced from measurements, and Category B, estimated by other means. In both categories, uncertainties are expressed as standard deviations and are denoted standard uncertainties. All category A uncertainty components are mutually independent and category A and B uncertainty components are independent (they are either from the same bin or they are from different bins), while category B uncertainty components are mutually fully correlated (e.g. uncertainty in power transducer in different bins).

In the standards [14], a theoretical basis for determining the uncertainty of measurement, using the method of bins is provided. Following this basis, the uncertainty components are either fully correlated (implying linear summation to obtain the combined standard uncertainty) or independent (implying quadratic summation, i.e. the combined standard uncertainty is the square root of summed squares of the uncertainty components.

A more simple classification for the errors is considered by Lackner et al. [20]:

The error could be considered as "random" when it is produced by variability in the quantity being measured or in the measurement procedure. In this case, the standard deviation of the measurements is a measure of the uncertainty of a single measurement due to random error. The errors for different values are often assumed to be independent and to have normal distributions about the true value

Other errors, called "systematic", or biases, are constant over a set of identical measurements and they are due to the measurement device itself. If the error is detected, then it is easy to correct the values. In this case, the uncertainty does not necessarily have to be characterized by a normal distribution, and therefore measured by the standard deviation. Nevertheless, if a collection of the same type of instruments is considered, the bias of this collection can be assumed to be independent (with respect to other instruments) and normally distributed with a mean value of zero .

Uncertainties can be characterized by the fractional standard uncertainty, which is a percentage uncertainty, and is calculated as the uncertainty of the measurements of a parameter divided by the absolute value of the expected value of the parameter. It is generally more convenient and intuitive to use the fractional standard uncertainty, since it is non-dimensional.

When multiple uncertain quantities are used to calculate some parameter *f*, the uncertainties in the component quantities combine to yield a total uncertainty in the parameter.

For a parameter *f*, that is a function of several variables, $f=f(x_1,\ldots, x_n)$, the uncertainties of the variables, $\delta x_1^*,\ldots, \delta x_n^*$ (a superscript * is used to denote absolute uncertainties), are combined to yield an overall uncertainty, δf, that is calculated using Eq. (16), as long as the uncertainties are independent. All uncertainties in Eq. (16) are absolute uncertainties, and so they can have units.

$$\delta f^* = \sqrt{\left(\frac{\partial f}{\partial x_1}\delta x_1^*\right)^2 + \cdots + \left(\frac{\partial f}{\partial x_n}\delta x_{1n}^*\right)^2} \tag{16}$$

Equation (16) is referred to as the "root-sum-square" (RSS) technique, and it is the standard method for combining independent uncertainties. Equation (16) can be non-dimensionalized so that the uncertainties are expressed as fractional uncertainties (Eq. 17), in which δf and $\delta x_1,\ldots,\delta x_n$ are now fractional uncertainties. The partial derivatives and the fractions, which multiply the fractional uncertainties, are referred to as "sensitivity factors," since they measure how sensitive changes in *f* are to changes in the variables. The sensitivity factors may be positive or negative in order to indicate if a change in the individual variable causes an increase or a decrease in *f*. The sign is not particularly important though, since the terms are then squared. The sensitivity factors are also non-dimensional.

$$\delta f = \sqrt{\left(\frac{\partial f}{\partial x_1}\frac{x_1}{f}\delta x_1\right)^2 + \cdots + \left(\frac{\partial f}{\partial x_n}\frac{x_n}{f}\delta x_n\right)^2} \qquad (17)$$

In this section, the different uncertainty sources will be addressed:

4.1. WIND RESOURCE UNCERTAINTY

This uncertainty is the overall uncertainty in the final estimation of the site specific hub height wind speed.

The process for this variable calculation was explained in section 3.1. The overall uncertainty will integrate all the uncertainties arising in each step of this calculation.

4.1.1 Wind Speed Measurement Uncertainty

This uncertainty comes from the measuring of the actual wind speed at a site.

Usually, the wind data are presented as series of 10-minute averages of the recorded wind speed (sampled at approximately 1 Hz.) The mean measured wind speed and all the following calculations in the wind resource assessment are based on these data base. Therefore, any uncertainty in the measurement process, will affect the final values.

The most important uncertainties in the wind speed measurement are due to the anemometer behavior (calibration, dynamic over-speeding, vertical flow effects and vertical turbulence effects), tower effects (e.g. mast shadow), boom and mounting effects, and data reduction accuracy.

The quality control analysis of the data accounts for these uncertainties and tries to correct, or at least, eliminate the wrong values (see section 3.1.1.)

4.1.2. Weibull fitting uncertainty

As it was explained in section 3.1.2, in the wind resource assessment it is usual to model the wind speed distribution using the theorical Weibull probability function.

The Weibull fitting uncertainty can be evaluated as any other adjustment error.

Morgan et al. [3] evaluate the goodness-off-fit of the distributions to the wind speed samples, using the coefficients of determination associated to de adjustment, observing the advantages of this parameter over other tests.

Another option for evaluating the goodness-off-fit is using the Kolmogorov-Smirnov test [9] and [16].

4.1.3. Long term Resource Estimation Uncertainty

This uncertainty includes the MCP correlation uncertainty, the changes in the long-term averages due to the global climate change, inter-annual variability, and uncertainty over the turbine life.

There are different methods for estimating the uncertainty in the MCP correlation, depending on the respective techniques employed. For instance, it can be calculated through the different fitting errors (see deliverable 3.1 [D3.1]):

The mean bias error (MBE)
The mean absolute error (MAE)
The distribution error (DE)
The root means squared error (RMSE).

These calculations could also be integrated into the code.

Other plots, as the relationship between the wind speed estimate variation and both the period of record and the correlation coefficient value, can be analysed.

Nevertheless, a high percentage of this uncertainty my come from the uncertainty in the reference data base itself (apart from the on-site measurements uncertainty), and from the differences in the scales between the reference and on-site data bases [6].

4.1.4. Hub height extrapolation uncertainty

The difference between the predicted and observed wind energy production might be up to 40% due to turbulence effects, wind data average period, and extrapolation from the reference height to hub heights.

Wind speed extrapolation might be regarded as one of the most critical uncertainty factor affecting the wind power assessment, when considering the increasing size of modern multi-MW wind turbines.

Moreover, this uncertainty is increased in the offshore environment by the inclusion of the dynamic surface and especial surface layer characteristics.

This uncertainty depends on different factors, as the data accuracy itself, the wind shear law application, and the atmospheric stability evaluation. Yves- Marie Saint-Drenan et al. [10] evaluate the importance of the temperature accuracy for the determination of the atmospheric stability, which affects the wind speed.

4.1.5. Wind resource assessment uncertainty

As it was explained in the introduction of the section 4.1, the overall uncertainty of a variable that is function of other independent variables, is calculated as the square root of the summed squares of the uncertainty components (RSS), taking into account their respective sensitivity factors.

Therefore, applying the non-dimensional equation 17, and considering all the wind resource uncertainties, the general equation to determine the overall uncertainty of the long-term hub height mean wind speed uncertainty *δU*, is shown in Eq. (18).

$$\partial U = \sqrt{\sum_i^N (SF_i \; x \; \partial U_i)^2} \qquad (18)$$

Where Ui are the respective N individual uncertainties and SF_i are their respective sensitivity factors for each category of uncertainty, which represent the partial derivatives and fractions that appear in eq. 17. The sensitivity factors measure how sensitive changes in U are to changes in each individual variable.

The sensitivity factor for most variables in the AEP_{NET} calculation process is equal to 1, except in the case of the wind speed measurement, because the measured wind speed is used to calculate the shear parameter, and the shear parameter is then used to estimate the long term wind speed at hub height. The result is that error in the measurement of the wind speed causes error in the shear parameter calculation, which then causes additional error in the estimate of long term wind speed at hub height. Thus, the contribution of measurement uncertainty to the total uncertainty is magnified due to shear extrapolation, and so the sensitivity factor for the measurement uncertainty is greater than one. It is important to emphasize that this effect is not due to any error in the wind shear model. Rather, it is a mathematical byproduct of using uncertain data to determine an extrapolation parameter.

In practice, the sensitivity factor for the measured wind speed is estimated from experience. But it can be calculated, as Lackner et al. propose [20].

4.2. ENERGY LOSS FACTOR UNCERTAINTY

The uncertainty analyses presented within the energy assessments, typically assume that the turbines will perform exactly to the defined availability and power performance levels.

The power performance and availability levels are usually covered by specific warranty arrangements, and hence any consideration of the uncertainty in these parameters needs machine-specific and contract-specific review, which is generally outside the scope of a ‘standard’ energy analysis. However, it is increasingly the norm to assign a moderate uncertainty to the estimated availability, loss factor and power performance factors, to reflect that small deviations from expected availability and power performance levels may not be sufficient to trigger damage payments under the warranty.

Although every loss factor calculation is an uncertainty process, in this section, only the wake losses and power performance uncertainties are going to be reviewed.

4.2.1. Wake losses uncertainty

The wake losses uncertainty is a combination of inputs and parameters uncertainty propagation, and a model inadequacy, also a function of the inputs.

Two benchmark campaigns have been carried out within the EERA-DTOC project on two different Danish offshore wind farms, Horns Rev and Lillgrund. The results show a relatively good agreement of the wind farm flow models with the measurement for wide degree bins, but a poor agreement for the small degree bins. Further investigations [17], [18] have indicated that the discrepancy between the model results and measurement results could be coming from a high uncertainty in the inflow wind direction estimation in the measurements.

At this stage, a consensus within EERA-DTOC has not been reached yet, and even less within the international community, on how to quantify the uncertainty of the wind farm flow model results. A main issue is that the flow model inadequacy has to be dissociated from the input uncertainty. This requires to estimate the inflow wind direction uncertainty accurately and to dissociate it from the measurement results, or alternatively to process the wind farm flow models with this inflow uncertainty [D1.3].

A parallel effort is going on through the IEA-Task 31 WakeBench project (within which a majority of the EERA-DTOC partners are participating) that should be finalized within the timeframe from EERA-DTOC project. IEA-Task 31 represents a much wider international participation for establishing a scientific consensus. It is therefore decided to follow closely this effort and to influence it in order to define more widely accepted guidelines on how to properly estimate wind farm flow model uncertainty.

In the meantime, it is suggested to use an uncertainty between 0.5% and 2% for the power uncertainty within a 30 degree bin, based on the estimate of Gaumond et al. [13] and the results of the two benchmarks.

4.2.2. Wind Turbine Power Production Uncertainty

Three sources of power production (labeled as $\delta P1$, $\delta P2$, and $\delta P3$) uncertainty can be considered:

1. Wind Turbine Specimen Variation
2. Wind Turbine Power Curve Uncertainty
3. Air Density Uncertainty

The power curve uncertainty is typically significantly larger than the other two uncertainties. When power curves for wind turbines are measured by the manufacturer, several factors contribute to the uncertainty in this measured power curve.

The primary factor is uncertainty in the wind speed to which the turbine is responding because the uncertainty in the actual power being produced is quite small.

The effect of turbulence on the IEC 61400-12-1 power curve was addressed in (among others) [21]. They showed that wind fluctuations generate deviations for the IEC power curve. This is due to the fact that the power curve is non-linear, and because data is averaged over (ten-minute) time intervals. Correction terms were defined, that take into account the statistics of the wind speed (turbulence intensity, higher-oder moments) and the expected power curve. Using these correction terms removes the deviations of the IEC power curve with varying wind conditions, e.g. turbulence intensity. This can be used only if the expected power curve is known (IEC power curve in the limit of no turbulence).

As a result of all described above and in section 3.4.4, the power curve will vary from one site to the next and depending on the meteorological conditions, but since the other influential variables are not measured and taken into account, the variation in the power curve will be appear as uncertainty.

The overall power production uncertainty can be calculated using the general equation given in Eq. (17). The three uncertainty sources are independent, and the sensitivity factor for each is one. Thus, the overall power production uncertainty, *δP*, is shown in Eq. (19).

$$\delta p = \sqrt{(\delta P_1)^2 + (\delta P_2)^2 + (\delta P_3)^2} \tag{19}$$

4.2.3. Overall Energy Loss factor uncertainty

The energy loss factors are assumed independent and normally distributed, and the overall energy loss factor uncertainty, *δELF*, can be calculated using Eq. (17), as long as the individual energy loss factor uncertainties, δELF_{AV}, δELF_{ELE}, δELF_{WAKE}, δELF_{TP}, δELF_{ENV}, and δELF_{Av}, are expressed as fractional standard uncertainties.

The sensitivity factor for each energy loss factor is one, since the overall energy loss factor is simply the product of the six individual energy loss factors. The resulting equation for *δELF* is given in Eq. (20).

$$\partial \mathrm{ELF} = \sqrt{(\partial ELF_{AV})^2 + (\partial ELF_{ELE})^2 + (\partial ELF_{WAKE})^2 + (\partial ELF_{TP})^2 + (\partial ELF_{ENV})^2 + (\partial ELF_{AV})^2} \tag{20}$$

4.3. OVERALL NET ENERGY YIELD UNCERTAINTY

Once the wind resource at a site has been determined, it is combined with a selected power curve and the energy loss factors to yield an estimate of the energy production of the wind turbine or wind farm (see sections 3.3 and 3.4).

The uncertainty in the wind resource, the power production, and the energy loss factors contribute to an overall uncertainty in the energy production δAEP_{NET}.

In order to calculate the uncertainty in the energy production δAEP_{NET}, the equation 10, 15 and 17 must be combined as follows:

$$AEP = \sum_i P(U_i)N_i \tag{10}$$

$$AEP_{NET} = AEP \times ELF \tag{15}$$

$$\delta f = \sqrt{\left(\frac{\partial f}{\partial x_1}\frac{x_1}{f}\delta x_1\right)^2 + \cdots + \left(\frac{\partial f}{\partial x_n}\frac{x_n}{f}\delta x_n\right)^2} \tag{17}$$

In this case, *f* is the AEP_{NET}, and therefore, the partial derivatives of AEP_{NET} with respect to the wind speed (U), wind turbine power (P) and energy losses (EFL) should be calculated, in order to estimate their respective sensitivity factors (SF_i) .

Considering that these uncertainty sources are independent, in practice, the overall Net Energy Yield uncertainty (δAEP_{NET}) is given by the equations (21) and (22), where the sensitivity factors for P and ELF are considered equal to 1

$$\partial \mathrm{AEP} = \sqrt{(\partial U)^2 + (\partial P)^2 + (\partial ELF)^2} \tag{21}$$

$$\partial \mathrm{AEP} = \sqrt{\sum_i^N (SF_i \ x \ \partial \mathrm{U}_i)^2 + (\partial P)^2 + (\partial ELF)^2} \tag{22}$$

In practice, all the individual uncertainty components are considered independent, and the overall uncertainty is calculated as the root-sum-square (RSS) of these individual uncertainty values, regardless the error source, as it is showed in the next section example.

5. PRACTICAL EXAMPLE OF NET ENERGY YIELD CALCULATION

As a practical example, RES prepared the following tables, in which different losses and uncertainties are considered to calculate the Net Energy Yield estimation for a Wind Cluster.

Reference Energy Yield	**1000**	**GWh**
Array Efficiency (Wakes)	91%	
Horizontal Wind Speed Extrapolation	101%	
Gross Energy Yield	**919.1**	**GWh**
TOTAL Gross-to-Net Loss Factor	**86.0%**	
Net Energy Yield	**790.8**	**GWh**
Total uncertainty on Net Yield	**7.3%**	

Individual Loss Factors (values are examples only)

Availability Turbine	95%
Availability Balance of Plant	99%
Availability Grid	99%
Availability Accessibility	98%
Availability Other	100%
Turbine Performance Power Curve	99.5%
Turbine Performance High Wind Hysteresis	99.70%
Turbine Performance Wind Flow	100%
Turbine Performance Other	100%
Electrical Losses	98%
Electrical Facility Consumption	100%
Environmental Performance Degradation Icing	100%
Environmental Performance Degradation Non Icing	99.50%
Environmental High Low Temperature	100%
Environmental Shutdown Due To Icing Lighting Hail Etc	100%
Environmental Site Access and Force Majeure	100%
Environmental Tree Growth Or Felling	101%
Curtailment Wind Sector Management	97.20%
Curtailment Grid And Ramp Rate	99.30%
Curtailment Power Purchase Agreement	100%
Curtailment Environmental	100%

Table 1.: Individual Energy Yield Loss Factors

Wind Speed to Energy sensitivity factor	**1.5**

Individual Uncertainty Components (values are examples only)

Wind Speed Uncertainty	*3.50%*
Energy Uncertainty due to Wind Speed	5.25%
Horizontal Extrapolation Uncertainty	1.50%
Extrapolation to Hub Uncertainty	0.80%
Wake Uncertainty	3.00%
Air Density Uncertainty	0.30%
Loss Factor Uncertainty	3.00%
Power Curve Uncertainty	2.00%
Substation Metering Uncertainty	0.50%

Table 2.: Individual Energy Yield Uncertainty Components

According to the tables, the

Gross Energy Yield = Reference Energy Yield x Array Efficiency (Wakes) x Horizontal Wind Speed Extrapolation

In this example, the Gross Energy Yield is

919.1 GWh = 1000 GWh x 91/100 x 101/100

Note that, in this case, the Wake effect is accounted for the Gross Energy Yield estimations, although it could be considered as another loss to be subtracted from the Gross Energy Yield to calculate the Net Energy Yield. Besides, it accounts for the horizontal Wind Speed extrapolation.

The Net Energy Yield is obtained by multiplying all the individual loss factors in the table 1 (TOTAL Gross-to-Net Loss Factor) by the Gross Energy Yield.

Net Energy Yield = Gross Energy Yield TOTAL x Gross-to-Net Loss Factor

In this example, the Net Energy Yield is

790.8GWh = 86.0/100 x 919.1GWh

According to the equation 22, The total Uncertainty (7.3%) is the Root Sum Square (RSS) of all individual uncertainty components in table 2, taking into account a sensitivity factor value (1.5) for the wind speed,

6. CONCLUSIONS

Some important conclusions from all described above are:

- There is a great variety of methods for each step in the Net Energy Yield estimation process.
- Even though the same method is used for one of these steps, the results can greatly differ, depending on the inputs and assumptions applied.
- In order to avoid the high differences in the Net Energy Yield estimation figure, an agreement should be reached, or at least, careful explanations about the employed procedure should be provided besides this figure,
- Each calculation (step) in the Net Energy Yield estimation process has an associated uncertainty.
- One of the most important uncertainty sources is the wind data base itself, and every Wind resource analysis should start from a quality control analysis, in which agreed rules should be applied.
- The total uncertainty of the Net Energy Yield is an important value, which must be provided besides the total amount, and depends on the individual uncertainties in each step.
- It is difficult to give a value for each one of these uncertainties, and an agreement should be reached on the procedure for their estimations.
- In practice, most uncertainties and loss factors are assumed as a standard values, from consultants' experience, but this practice should be avoided, because their estimation depends on the particular site and project, and could lead to important errors that trigger unintended consequences for risk estimation.
- The Net Energy Yield estimation must be adjusted to the particular site and, especial care must be paid for offshore places, because of the great differences in the atmospheric boundary layer.

The main conclusion from this deliverable is the need for an agreement on the procedures for the Net Energy Yield estimation, including its uncertainty and losses, which avoid the great differences among the figures given by different consultants.

It is difficult to integrate the different procedures for the Net Energy Yield estimation into a code, since each method allows for different options and inputs, which should be provided by experts. Nevertheless, it should be possible but, at the moment, only for some of these procedures.

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