Global Sensitivity Analysis for Offshore Wind Cost Modelling

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Abstract

The costs of offshore wind are decreasing rapidly. However, there is a need to better understand the key drivers behind these cost reductions. New environmental regulations, economic policies, technological advancements and financing structures have resulted in a set of relationships that need to be considered in order to define risks and profitability for the next generation of offshore wind farms. We use an industry-leading offshore wind cost modelling tool which integrates site characteristics, technology specificities and financial modelling expertise and apply state-of-art global sensitivity analysis methods for different classes of offshore wind farms, ranking the contribution of around 150 input parameters that influence the cost of offshore wind development. We show that the top 5 parameters when building an offshore wind investment business case are the wind speed, target equity rate of return, turbine costs, drilling costs and debt service coverage ratio. The contribution of this paper can help guide additional efforts towards reducing the uncertainty of those key parameters to decrease costs and provide a framework to choose global sensitivity analysis techniques for offshore wind techno-economic models.

Keywords: Global sensitivity analysis, Offshore wind cost modelling, decision-making under uncertainty

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1 Introduction

By the end of 2018, the European offshore wind market had installed a cumulative total capacity of more than 18GW. Within Europe, the UK is the market leader for offshore wind, responsible for 43% of the total number of all grid-connected turbines.[1] To sustain this leading position in the market, a Levelised Cost of Energy (LCOE) target of £100/MWh was set jointly by the UK government and industry in 2012,[2] which was expected to be met by 2020. However, four years ahead of schedule, wind farms taking final investment decisions in 2015/2016 were already achieving prices lower than this target, not just in the UK but across Europe. In continental Europe, record-low contracts for offshore wind farms were awarded to Borsselle 3 and 4 offshore wind project in the Netherlands at 54.5€/MWh in July 2016 and Kriegers Flak in Denmark at 49.9€/MWh in November 2016. Following these, competitive tenders for feed-in subsidies in Germany resulted in bid prices of 0€/MWh in April 2017. In the UK, the Contract for Difference (CfD) Allocation Round (AR) 2 resulted in the lowest strike price seen at that moment with a value of £57.5/MWh in September 2017, down from a lowest £114.39/MWh in CfD AR 1 in February 2015. In April 2018 in the second German auction, results once again included zero subsidy bids. In September 2019 in the UK CfD AR 3, prices dived to a staggering value of £39.65/MWh, 60% lower than the target imposed to be met by 2020. Since the details of subsidy schemes vary it is not possible to directly compare them across countries, but as figure 1 shows for the UK, cost reductions have been very rapid.

In addition to these rapid cost reductions, offshore wind support mechanisms are also changing, with a general trend towards regularly scheduled auctioning systems for offshore wind feed-in tariffs or contracts for differences. The UK government, for example, has committed to a series of CfD auctions starting in May 2019 and every other year from then on.[3] The combination of rapid cost reductions and the transition to central auctioning systems has pushed developers to make cost predictions further into the future, increasing the level of uncertainty in their estimates and challenging the way offshore wind cost modelling has previously been addressed. Changing environmental regulations and financing structures have furter complicated cost modelling.

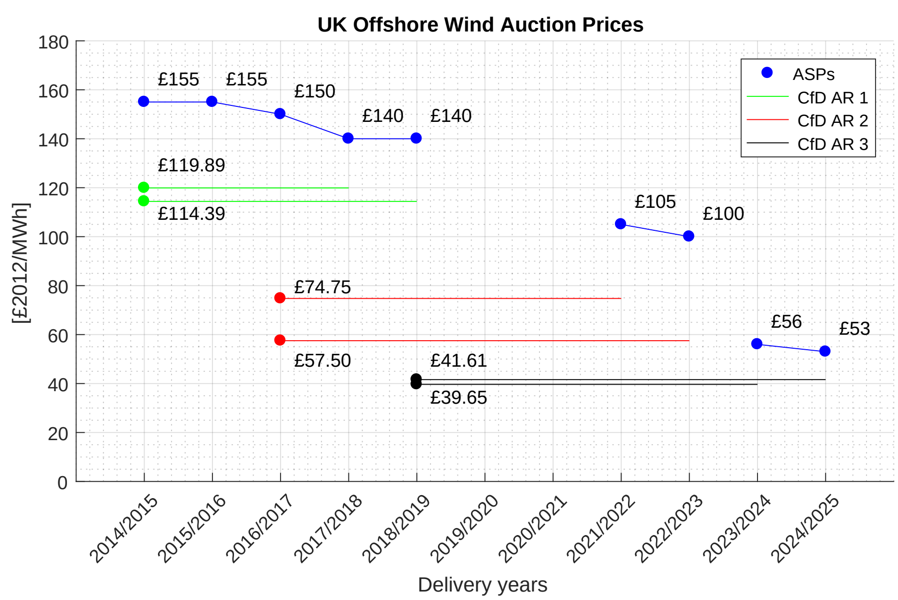


Figure 1: UK Contract for Difference Allocation Round Results

As the offshore wind market continues to thrive, a wider range of products is being offered to developers; more reliable sensing devices to measure the wind speed, taller, bigger and more powerful wind turbines, higher voltage inter-array systems, new bottom-fixed and floating foundation designs, longer export cables, better O&M strategies and data-driven solutions to operate the farms, advanced types of financing, etc. This increased variety of technology and product choices has resulted in an increased complexity for project developers to make decisions regarding the optimal selection of technology and products for a given site. In addition to the increased variety, the unprecedented pace of the sector is pushing developers to conduct periodical market research reports to keep up with the latest technological trends, as there is room for accommodating innovations in the design of the farms due to long development periods before commissioning. The case study in Section 5 will shed light on which parameters are key when building offshore wind investment business cases.

The first studies to assess the techno-economic and financial viability of offshore wind farms were based on projecting onshore data to offshore developents.[4] In doing so the models did not account for specific offshore parameters and consequently, did not represent the harsh environmental conditions offshore wind farms operate in. As the industry started to grow, developers, contractors and suppliers invested time and resources to come up with new cost models tailored to the sector. In parallel, local sensitivity analysis and probabilistic techniques were applied to those in order to quantify key cost drivers and their associated uncertainties.[4–6] Since then, both commercial and academic models have attempted to estimate offshore wind capital costs, operational expenditure and LCOE.

LCOE is a theoretical metric and it therefore has a number of weaknesses associated with it;[7] for example, it does not take into consideration wider system benefits or costs nor does it deal with variability and intermittency. An example related to variability and intermittency is the process whereby an offshore wind developer strikes a Power Purchase Agreements (PPA) deal with a buyer. PPAs impact the LCOE in ways that are no accommodated in existing cost models through penalties imposed by contractual arrangements.[8] In addition, as the analysis looks at the project's LCOE in isolation, it excludes any potential synergies with the existing portfolio of energy projects. Therefore, this metric might become less relevant as the penetration of renewables into the energy system increases and projects are designed to add value to and complement the aggregated portfolio of energy projects.

In 2012, the UK government published a simple LCOE model to assess the impact of innovations on a generic offshore wind farm. A stochastic version of that model was implemented in Excel by means of the @RISK extension.[9] In addition, a local sensitivity analysis was carried out to identify the impact of several uncertain input parameters. Given the fundamentally multidisciplinary nature of cost modelling, many approaches have since been followed to develop new models. Whereas cost modelling engineers tend to place more emphasis on a detailed breakdown of the different offshore wind farm components, as shown in,[10,11] investors typically take a high-level approach on technology and focus on the specificities of the financing conditions, as shown in.[12,13] Global sensitivity analysis has already been applied to offshore wind techno-economic models. Whereas[14] used screening techniques to assess the sensitivity of operation and maintenance costs,[15] used variance-based techniques to assess the sensitivity of capital and operation and maintenance costs.

Despite these attempts to capture offshore wind technicalities, the introduction of new environmental regulations and economic policies, rapid technological advancements, and financing structures has resulted in a new set of relationships that need to be considered in order to define risks and profitability for the next generation of offshore wind farms. For these reasons, simple cost models are no longer suitable to accurately represent these relationships, when being used as decision-making tools. Instead, tailored techno-economic models are being developed, integrating site characteristics, technology specificities and financial modelling expertise. These models are very complex, resulting in relationships between inputs and outputs that are poorly understood and cannot be explored by simple intuition alone. Formal sensitivity analysis, and in particular, global sensitivity analysis (GSA) methods are therefore necessary.

GSAs determine the system's critical points in the combined space formed by the parameters.[16] They are rapidly gaining traction in different fields.[17] For the purposes of this paper, the GSA helps determine which input parameters most significantly impact model outputs. Ranking the input parameters in order of their effect on model outputs (known as as *Factor Prioritization*[18]) provides useful insight, especially if the model is complex and/or still in development. The factor prioritization process may show that variation in a subset of input parameters has such a small impact on outputs that uncertainty in these parameters can safely be ignored. This is a common result, as the sensitivity of model outputs to input parameters often follows a highly asymmetric distribution, with a small subset of inputs paremeters being responsible for most of the output variation, while most inputs play no significant role.[19] In further model development, model complexity can then be reduced by ignoring potential variation in insignificant input parameters, a process known as *Factor Fixing*.[18] In this paper, we employ both factor prioritisation and factor fixing. For a detailed discussion of more GSA techniques in general, see.[18, 20–23]

To our best knowledge, state-of-art GSA methods have not been applied to complex techno-economic offshore wind cost models. Therefore, the aim of the current paper is to remedy the lack of understanding of the relationship between offshore wind cost modelling input and outputs by using state-of-art global sensitivity analysis techniques combined with an advanced stochastic cost modelling tool to investigate the most relevant parameters influencing cost and uncertainty in the design of offshore wind farms. Doing so, it makes two contributions to existing knowledge. First, it presents a consistent method for state-of-art applications of GSA in offshore wind cost modelling, which will be of use to cost modellers. Second, through applying this method, it investigates which variables are the most important drivers of offshore wind costs, contributing to the literature on reasons behind cost reductions and informing where additional efforts to reduce cost levels or variability can further reduce LCOEs.

The remainder of this paper is structured as follows: Section 2 starts with the description of the stochastic framework, Section 3 reviews the state-of-the-art GSA techniques in terms of its use and suitability for the cost modelling tool. Section 4 introduces the variance-based and PAWN distribution-based GSA techniques. These techniques are then applied to a case study in Section 5, where the contribution of around hundred fifty parameters in the cost and uncertainty of offshore wind farms is assessed. Finally, results and conclusions are drawn in Section 6.

2 Stochastic Cost Modelling

The modelling approach to assess the impact of input parameter variation on offshore wind costs is based around the Offshore Wind Cost Analysis Tool (OWCAT) developed at the EDF Energy R&D UK Centre. OWCAT has a modular design and its structure is represented in Figure 3. Further information regarding its inputs, outputs and the processes that link them can be found in.[24] Although specific to EDF Energy's requirements, the model is representative of state-of-art offshore wind cost models used throughout the offshore wind sector. The cost modelling tool integrates site characteristics, technology specificities and financial modelling expertise in a more detailed manner than existing cost modelling tools in the literature that do not have access to the data and expertise from the offshore wind sector.

The transition from deterministic to stochastic models requires an added level of complexity that can only be justified if the three following basic features exist.[19] First, a deterministic model must exist. Second, there must be a variety of sources of uncertainty affecting the model inputs. Third, there must be a need for GSA methods, i.e., decision-making processes that motivate the uncertainty assessment. All of these are met; the OWCAT model is already in use, its inputs clearly include uncertain parameters, including future costs across the supply chain, and improving understanding of cost and uncertainty in the design of offshore wind farms is urgently required.

OWCAT is a numerical model linking inputs (uncertain $\underline{x}$ or fixed variables $\underline{d}$) to outputs $\underline{z}$ (from which decision criteria can be established). This can be formally defined in Equation 1.

$$\underline{x}, \underline{d} \Longrightarrow \underline{z} = OWCAT(\underline{x}, \underline{d}) \tag{1}$$

It is worth noting the difference between these two set of inputs. Whereas some inputs have uncertainty associated to them, others may be fixed – as they will play another role in the model, those are represented with notation $\underline{d}$. This is the case when: (i) input parameters represent variables under full control of the developer: for example, the number of pinpiles of a jacket foundation, (ii) the uncertainties affecting the model inputs are considered to be negligible and (iii) the decision process conventionally fixes some variables for comparative purposes and time constraints: for example the discount rate may be set by the developer or state. However, it is important to bear in mind that a distinction between "uncertain" and "fixed" variables usually involve an iterative process by means of sensitivity analyses of the model which is out of the scope of this paper.

The methodology of quantitative uncertainty management is a staged process, which is represented in Figure 2. First, the specification of the problem needs to be considered. This is mathematically represented as the OWCAT model or Step A. After that, Step B consists in characterizing and quantifying the uncertain inputs modelled by probability distributions. Once this is done, the propagation of uncertainty sources to the quantities of interest outputs can be carried out. As shown in Figure 2, Step C can be performed in both directions: C representing the propagation of uncertainty sources to the outputs and C' representing the feedback from output to input variable probability distributions. In this paper, we will focus on step C' in order to understand the influence or rank the importance of the main cost drivers. This will allow the model user to identify the key variables for cost and uncertainty in the design of offshore wind farms. Furthermore, at this stage this could mean that 'uncertain' variables could be shifted to 'fixed' variables and the other way around in future studies, depending on the results of the global sensitivity analysis.

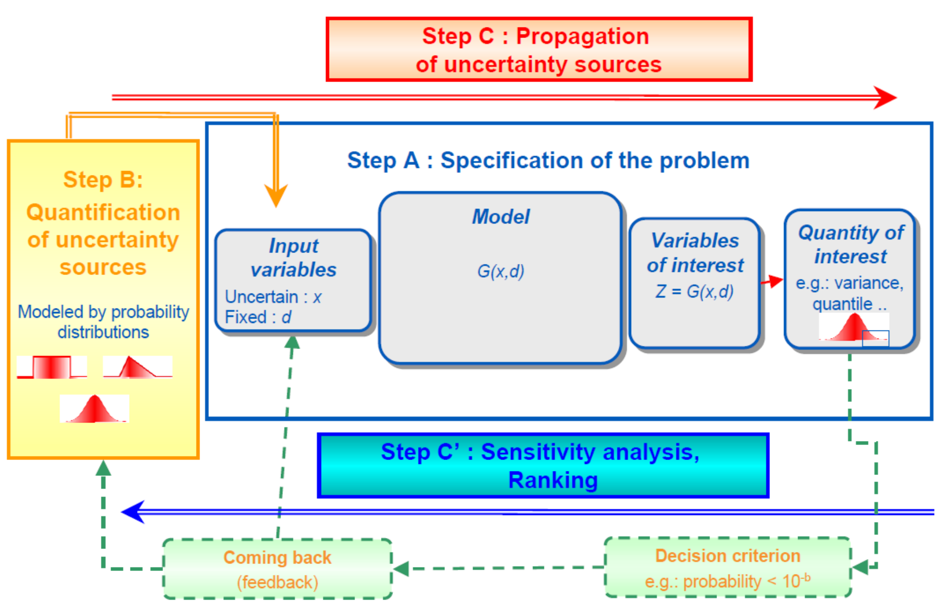


Figure 2: Uncertainty Management- The Global Methodology[25]

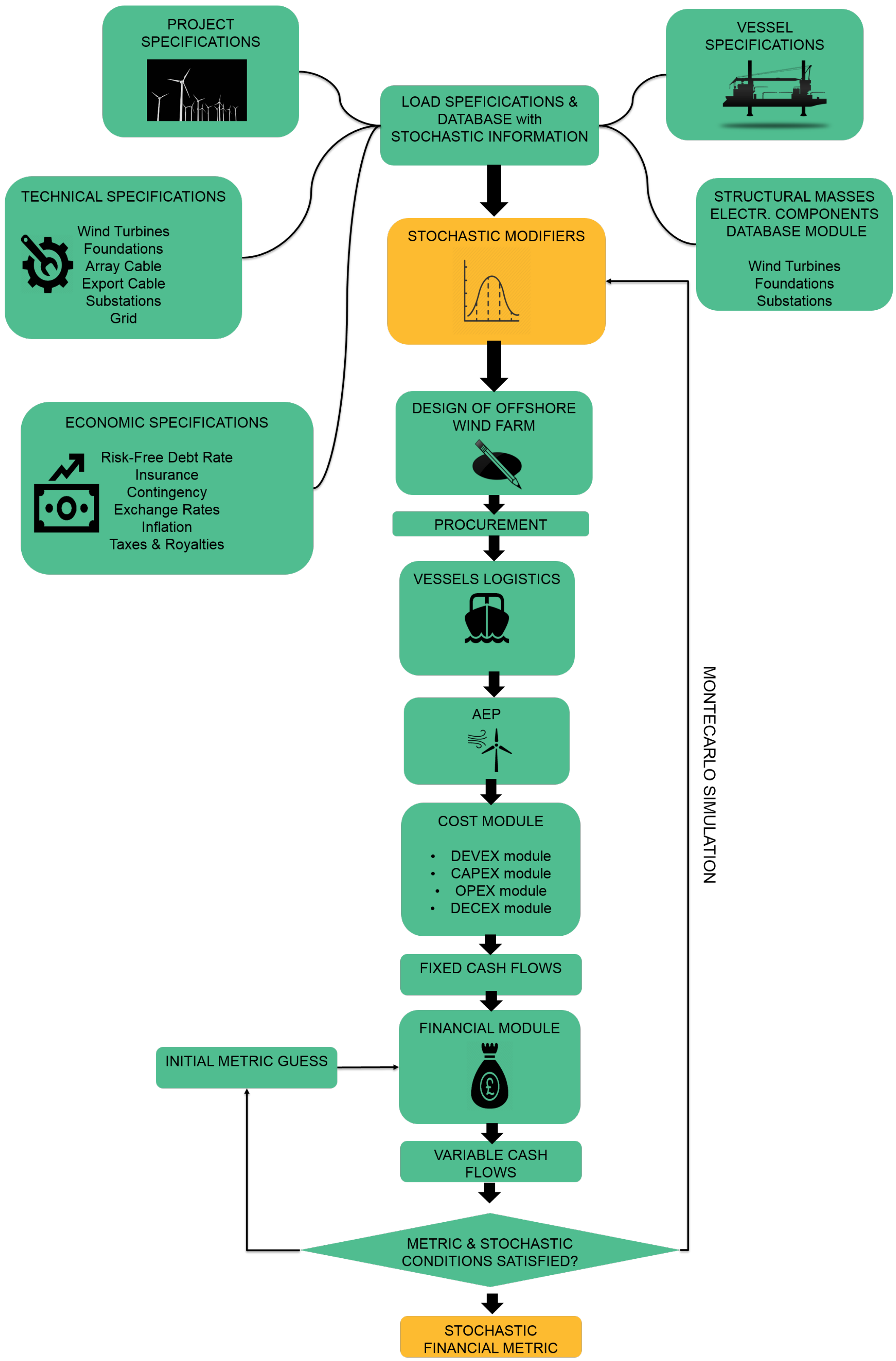


Figure 3: OWCAT structure

3 In Search Of GSA Methods For Offshore Wind Cost Models

Complex techno-economic offshore wind cost models such as OWCAT consist of many input variables linked by a large number of functions or algorithms. An example of GSA methods applied to a techno-economic model can be found in;[26] this study applies the variance-based, δ density-based and entropy density-based GSA methods to a simple biodiesel production model. Other authors have used a combination of methods at different stages of modelling; an example of those can be found in,[27] where the author applies different GSA methods to the aero-elastic time domain response of an offshore wind turbine. As far as offshore wind techno-economic models are concerned, an O&M model was investigated by means of the Morris method in[14] and a life-cycle cost model was interrogated by means of the variance-based Sobol method in.[9] An extensive review of different sensitivity analysis methods has been carried out and displayed in the Appendix in Table 4. From that, a flowchart has been drawn and displayed in Figure 4. The aim of the flowchart is to facilitate the choice of sensible sensitivity analysis techniques for a particular model, based on the following questions:

- Properties of the pre-existing model. Is the model linear or non-linear? is the model monotonic or non-monotonic?
- The number of inputs or CPU time. This will, to some extent, condition the number of model evaluations that can be undertaken in order to characterize the behaviour of the model.
- The goal of the study. Does the study need to be qualitative or quantitative? local or global? does it need to capture the interactions between parameters?
- The methodology to represent uncertainty. Is variance a good measure to represent the uncertainty in the model? This concerns the moment independent property.

The model we use for our case studies, OWCAT, is non-linear and non-monotonic and hence, no a priori assumptions can be stated. Since the model is composed of many different inputs, a screening technique has been considered appropiate for factor fixing, as Figure 4 suggests. However, more recently, Campolongo[28] has shown that it is better to use the total sensitivity indices of the variance-based method at low sample sizes, instead of the Morris method which implies many modelling assumptions. The same study suggests a unified practice when transitioning from screening to quantitative sensitivity analysis, using the same experimental design and sampled parameter instances to move from the former to the latter. This is the reason why in Figure 4 we have linked the screening techniques with the variance-based Sobol method. The same figure starts off by requesting assumptions on model properties. If our model was linear or non-linear but monotonic, several sensitivity analysis techniques could be applied in a very efficient manner by exploiting the internal structure of the problem. However, as is common for models of this type, in our case there is no prior knowledge on the behaviour of OWCAT. OWCAT is made up of different modules with highly non-linear functions and internal iterative processes. These include (a) cost modelling functions depending on exponents; (b) mass foundation and electrical components correlations also depending on exponents; (c) double loop iterative process for advance project finance modelling requirements, among others. As a result, only the right hand side of Figure 4 is appropriate. We are interested in using a global quantitative assessment that takes into consideration interactions between the different input parameters. Also, we would like to see how the contribution of model inputs to the output might change when considering the cumulative distribution function instead of variance to represent output uncertainty.

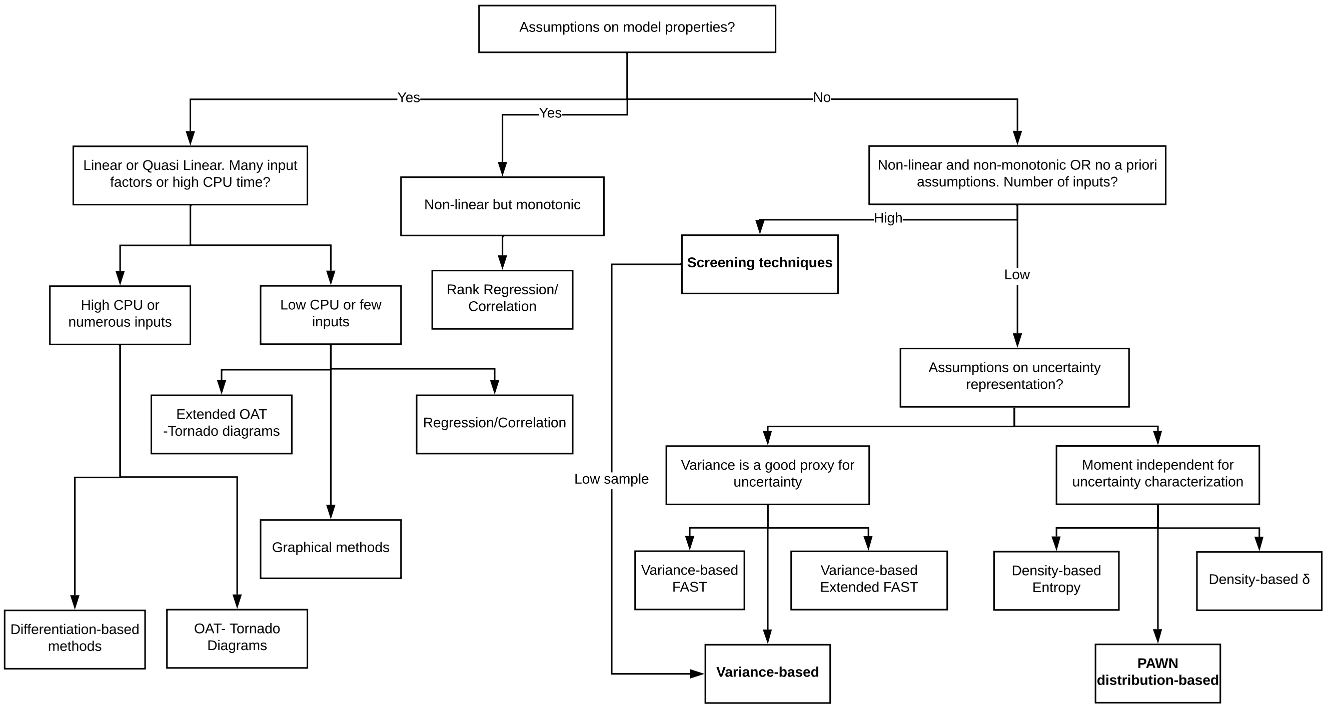


Figure 4: Decision diagram guiding the choice of SA techniques, expanded from[19]

Given the current state-of-the-art in GSA methods, it is appropriate to apply GSA methods to OWCAT in two stages. The first stage applies the variance-based method at low sample size to screen out irrelevant inputs, whereby the complexity of the input domain is reduced - this is the factor fixing stage. Then, the second stage applies the variance-based method and the PAWN distribution-based method to the subset of relevant inputs to identify which key inputs drive the response of the model, i.e., factor prioritisation. We compare the PAWN distribution-based method to the variance-based method in OWCAT, given that the latter is model-independent. A theoretical benchmark of these two methods was conducted in previous work.[29] The overall GSA process is displayed in Figure 5.

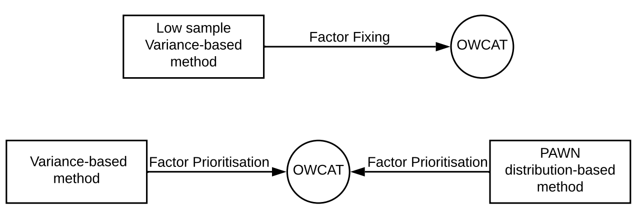


Figure 5: SA techniques chosen for OWCAT

4 GSA methods

4.1 Sobol method

The Sobol or variance-based method aims to decompose model output variance by the variance of model input parameters. Following[30] and its extension to non-uniform random variables in,[31] we assume that the model in question can be represented by a High Dimensional Model Representation (HDMR) as in Equation 3, which is made up by summands which are increasing in dimensionality. The total number of summands is equal to 2^N. Since the X_i variables are independent, the joint probability distribution function $f_X(\mathbf{X})$ is the product of the marginals, as displayed in Equation 2:

$$f_X(\mathbf{X}) = f_1(X_1)f_2(X_2)...f_n(X_N) \tag{2}$$

where $g(\mathbf{X})$ is the model to which the GSA is applied, and the number of elements of increasing dimensionality is an increasing function of $\binom{N}{i}$ $\forall i \in 1, ..., N$.

$$Y = g(\mathbf{X}) = g_0 + \sum_i g_i(X_i) + \sum_{i<j} g_{i<j}(X_i, X_j) + ... + g_{12...n}(X_1, X_2..., X_N) \tag{3}$$

If the model variables are mutially independent (i.e. if Equation 4 holds), the model representation is an Analysis of Variance (ANOVA) HDMR. In,[32] Sobol proves that, in this case, this decomposition is unique for any $k = 1, 2, ..., s$, and any $1 \leq i_1 < i_2 < ... < i_s \leq N$ and $s = 1, 2, ..., N$.

$$\int g_{i_1...i_s}(X_{i_1}, ..., X_{i_s}) f_{i_k}(X_{i_k}) dx_{i_k} = 0 \tag{4}$$

If, in addition, $g(\mathbf{X})$ and all its terms are square integrable, then the expectation and total variance of this function is given in Equation 5 and 6, respectively.

$$\mathbf{E}[Y] = \int g(\mathbf{X}) f_X(\mathbf{X}) dx = g_0 \tag{5}$$

$$\mathbf{V}[Y] = \int (g(\mathbf{X}) f_X(\mathbf{X}))^2 dx - {g_0}^2 \tag{6}$$

Partial variances V_i and the total variance $V[Y]$ can then be calculated as in Equations 7 and 8.

$$V_i = V(g_i(X_i)) = \mathbf{V}_{X_i}(\mathbf{E}_{\mathbf{X_{\sim i}}}[Y|X_i]) \tag{7}$$

$$\mathbf{V}[Y] = \sum_i V_i + \sum_{i<j} V_{i,j} + ... + V_{12...n} \tag{8}$$

The decomposition of the variance allows users to define the first order and total order sensitivity indices. The first order index S_i indicates the reduction in output variance that can be achieved by fixing input parameter X_i, disregarding interactions with other parameters, i.e. it is a mesaure of the main effect, as shown in Equation 9.

$$S_i = \frac{\mathbf{V}_{X_i}(\mathbf{E}_{\mathbf{X_{\sim i}}}[Y|X_i])}{V(Y)} = \frac{V_i}{V(Y)} \tag{9}$$

where X_i is the i-th factor. The expected value of Y is calculated by varying all $X_{\sim i}$ while keeping X_i constant. In an outer loop over all possible values of X_i, the outer variance can then be computed. Note that the number of compututations increases exponentially in the number of uncertain parameters. In a high-dimensional model, computing all Sobol components can therefore quickly lead to prohibitive computational costs.[33] therefore introduces the total effect index, as defined in Equation 10. This measures the total contribution of the variation in outputs that can be attributed to factor X_i, through not only the first order effect but also through all higher-order interactions.

$$S_{T_i} = \frac{\mathbf{E}_{\mathbf{X_{\sim i}}}(\mathbf{V}_{X_i}([Y|X_{\sim i}])}{V(Y)} = 1 - \frac{\mathbf{V}_{\mathbf{X_{\sim i}}}(\mathbf{E}_{X_i}([Y|X_{\sim i}])}{V(Y)} \tag{10}$$

Following the introduction of the Sobol method, many studies have attempted to increase the efficiency of the computational process. Two of the latest advances are radial sampling[28] and winding stairs.[34] Since these studies show that the latter outperforms the former, we use the winding stair design. Using this method, the total sensitivity indices S_{T_i} can be estimated by 11 and 12 respectively,[35] where $\mathbf{A}$ and $\mathbf{B}$ are independent sampling matrices with elements a_{ji} and b_{ji}, $j \in [1, ..., N]$ and $i \in [1, ...k]$ is a dummy variable, $\mathbf{A_B}^{(\mathbf{i})}$ is a transformed $\mathbf{A}$ such that column i belongs to $\mathbf{B}$, while the generic elements of the matrix are determined using quasi-random numbers, or the so-called shifted LP_t sequences. This process significantly improves the computational cost of the Sobol method compared to conventional Monte Carlo sampling, and open-source libraries exist to facilitate the generation process of the low-discrepancy series.[36]

$$\mathbf{E}_{\mathbf{X_{\sim i}}}(\mathbf{V}_{X_i}([Y|X_{\sim i}]) = \frac{1}{2N}\sum_{j=1}^{N}[f(\mathbf{A})_j - f(\mathbf{A_B}^{(\mathbf{i})})_j]^2 \tag{11}$$

$$\mathbf{E}_{\mathbf{X_{\sim i}}}(\mathbf{V}_{X_i}([Y|X_{\sim i}]) = \frac{1}{2N}\sum_{j=1}^{N}[y({a_1}^{(j)}, {a_2}^{(j)}, ..., {a_k}^{(j)}) - y({a_1}^{(j)}, {a_2}^{(j)}, ..., {b_i}^{(j)}, ..., {a_k}^{(j)})]^2 \tag{12}$$

4.2 PAWN distribution-based method

The PAWN distribution-based method assesses the difference between the unconditional cumulative distribution function (UCDF) $F_y(y)$ and the conditional cumulative distribution function (CCDF) $F_{y|x_i}(y)$ of output y when each input parameter x_i is fixed. This absolute value for a particular realisation of x_i is the Kolmogorov-Smirnov (KS) statistic, as defined in Formula 13 . This KS statistic provides an alternative measure of the impact of variation in x_i on model output variability. When it is close to zero, this implies that fixing input x_i does not significantly reduce output variance, and therefore, that variation in x_i can safely be ignored.

$$KS(x_i) = |F_y(y) - F_{y|x_i}(y)| \tag{13}$$

Note that the KS statistic is calculated locally, i.e. it may depend on the particular realisation of x_i. To convert it into a useful metric that is not dependent on arbitrary assumptions, it is therefore necessary to instead use its mean or median, given all possible realisations of x_i; so in general this is represented in Equation 14 as:

$$T_i = stat_{x_i}|KS(x_i)| \tag{14}$$

where $stat_{x_i}$ is the chosen statistic. T_i is now a global estimate of the impact of fixing x_i on the variation in model output. It is also moment-independent, in contrast to the variance-based methods described above, easy to interpret and stable. Since computing all $KS(x_i)$ is generally impossible, it is usually approximated numerically as $\widehat{KS(x_i)}$, as shown in 15.

$$\widehat{KS(x_i)} = |\widehat{F_y(y)} - \widehat{F_{y|x_i}(y)}| \tag{15}$$

We can then split the distribution of x_i into n equally spaced intervals I_k and define conditional samples $F_{y|x_i}$. The unconditional sample $F_y(y)$ can coincide with the entire sample Y or consist of only a subsample. This is represented in Equation 16. Further information regarding the latest PAWN method can be found in.[37]

$$\widehat{T_i} = stat_{k=1,\ldots,n}KS(I_k) \; where \; KS(I_k) = |\widehat{F_y(y)} - F_{y|x_i}\widehat{(y)} \in I_k| \tag{16}$$

Both the T_i and S_{Ti} metrics range from 0 to 1.

5 Case Study

A key metric for the life-cycle costs of an offshore wind project is the Levelised Cost of Energy (LCOE), defined as the discounted sum of the cash flow expenditures divided by the discounted sum of electricity production over the life span of the project. In order to calculate the LCOE, DEVEX, CAPEX, OPEX as well as DECEX have to be assessed. These costs are highly influenced by the physical characteristics of the wind farm, including but not limited to the water depth, distance from shore, wind speed and seabed conditions. Throughout the case study we consider the LCOE as the metric of interest. Therefore, we are interested in evaluating how different techno-economic model inputs affect the LCOE.

The purpose of the case study is to identify the main parameters for the development of an offshore wind farm, once an area has been awarded to the developer. For this reason, two theoretical offshore wind farms have been considered. Given that the average size of European commercial offshore wind farms commissioned in the year 2017 is 500MW;[1] the same size is chosen as a reference in our case study. The case study considers two types of commercial offshore wind farms. Type A is representative of UK Round 2 site allocations, whereas site type B is similar to the Scottish Territorial Water and UK Round 3 sites. We have assumed that there is a trade-off between how close the farm is from shore, its water depth and the wind resource available. Site Type A is most suitable for monopile foundations, since the seabed soil conditions are simple and drilling operations are kept to a minimum. At site Type B, on the other hand, jackets are the most cost-effective foundation, as seabed soil conditions are complex. To simplify the analysis, we assume that export cable lengths and vessel movement paths are equal to the closest distance to shore. Another assumption is that both offshore wind projects use project finance. Both sites are to be assessed with a generic 8.3 MW wind turbine with a rotor diameter of 164m. The project specifications for those generic offshore wind farms are shown in Table 1 and based on a report from The Crown Estate.[38] Apart from the fixed variables chosen to represent Site Type A and B, a list of the categories of uncertain variables used in OWCAT is given below.

Parameter	Site Type A	Site Type B
Water Depth [m]	25	45
Distance from shore [km]	25	35
Wind Speed @ 100m [m/s]	9	9.5
Foundation Type	Monopile	Jacket
Electrical Infrastructure	HVAC	HVAC
Wind Turbine Type	164-8.3 MW	164-8.3 MW

Table 1: Site Type A and B

- Project specifications, which refer to the offshore wind project characteristics. Examples of these would be the uncertainty regarding the wind speed at a given height, the average water depth, soil conditions, spacing between turbines, the length of the onshore cable route, etc.
- Technology specifications, which address the technological details of the wind turbine, foundation, inter-array cable, export system and grid connection. This includes the turbine availability, the average loading, installation and commissioning time of the different components, etc.
- Economic specifications, which include the the risk-free rate and cost of debt, insurance costs, contingency requirements, taxes, depreciation rates, seabed rent, exchange rates and inflation.
- Vessel specifications for all vessels used during installation and decommissioning. This includes day rates, vessel transit speeds, positioning time, mobilisation time, weather window requirements and carrying capacities.

6 Results

First stage - Factor Fixing
With the objective of screening out irrelevant inputs, the variance-based method (at low sample size) is applied to approximately 150 model inputs; this is described in Section 3 as the first stage GSA. We have used a high performance computing cluster at the University of Edinburgh to compute the total indices with 300 000 model evaluations. The same process is employed for both Type A and Type B offshore wind farms, with the only difference that Type A has 149 uncertain parameters whereas Type B has 150.

Figure 6 shows the total contribution of factor X_i to the LCOE variation, in descending order of importance. Note that Figure 6 does not show the contribution of the first factor, the measured (P50) annual mean wind speed, given that it is two orders of magnitude higher than the rest, which would distort the figures. Total sensitivity indices S_{Ti} (small circles in blue) are estimated via Monte Carlo simulation (using the Sobol low-discrepancy sequence described above) for input factors X_i i = 1,...,149 for Type A (150 for Type B). 95% confidence intervals (vertical dashed lines in blue) are estimated by bootstrapping 1000 replicas. Figure 6 highlights that the distribution of input parameter importance follows a highly asymmetric distribution, with a small number of input parameters accounting for most of the variation in output, while most inputs play little to no role. If we were to sum the separate S_{Ti} contributions of the different inputs, we would see that, for the cost modelling tool, these do not add up to 100%. As a result, the cost modelling tool features interaction between parameters. Only additive models, models that have no interactions between inputs, can be decomposed in terms of the contribution of individual inputs - the sum of the S_{Ti} contributions of the different inputs would add up to %100. The results of the global sensitivity analysis highlight the importance of the mean wind speed uncertainty in the design of offshore wind farms; S_{Ti} for the measured (P50) annual mean wind speed is 91% for Type A (89% for Type B). In addition to that, the five key inputs in Type A add up to 98% of S_{Ti}, whereas the sum of the rest of the inputs amount to 1%. Type B follows a similar result, where the five key inputs add up to 100% of S_{Ti} and the rest of the inputs 3%. As previously mentioned, these results demonstrate the very asymmetric distribution of importance in offshore wind investment models. We use a threshold S_{Ti} of 0.02% to select the relevant inputs for the second global sensitivity analysis phase: a benchmark between the PAWN distribution-based method and the variance-based method. As a result, 20 model inputs were selected for Type A and 22 for Type B.

Second stage - Factor Prioritisation
In order to enable a fair comparison between the PAWN distribution-based method and the variance-based method, the same number of model evaluations is considered; this is the second stage of the GSA. The benchmark is carried out by applying the PAWN distribution-based method with 20 conditioning points, against the variance-based with the selected parameters from the previous analysis, resulting in approximately 300 000 model evaluations for each method.

The top chart in Figure 7 displays the total contribution of the LCOE variation due to factor X_i in ascending order of importance for the variance-based method. Total sensitivity indices S_{Ti} (small circles in blue) are estimated via a Monte Carlo simulation (again using the Sobol low-discrepancy sequence) for input factors X_i i = 1,...,20. 95 % confidence intervals (vertical dashed lines in blue) are estimated by bootstrapping 1000 replicas. The bottom chart in Figure 7 displays the total contribution of the LCOE variation due to factor X_i in ascending order of importance for the PAWN distribution-based method. Total Kolmogorov Smirnov (KS) statistics T_i (small circles in blue) are estimated via random sampling, and confidence intervalswere estimated using bootstrapping as before. To capture the level of noise for the PAWN distribution-based method (vertical dashed lines in red), we use a dummy variable which is bootstrapped 1000 times, resulting in the upper and lower horizontal dashed lines in red. This does mean that, if T_i is below the upper bound, we cannot distinguish between this happening because of the importance of the input, or because of the level of noise. The same process is repeated for Type B offshore wind farm for the 22 selected inputs and displayed in Figure 8.

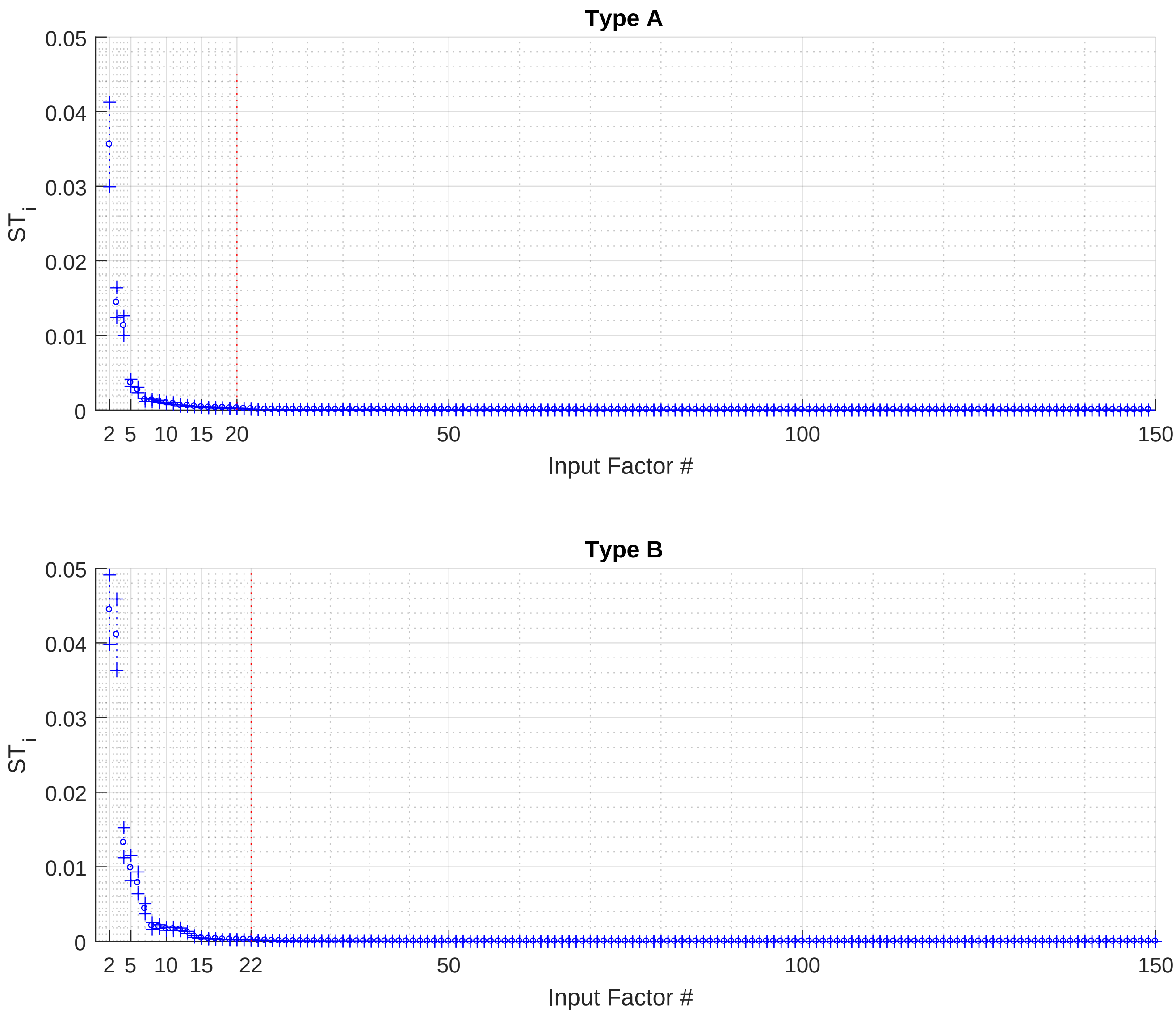


Figure 6: First stage global sensitivity analysis applied to OWCAT for Type A and B offshore wind farms. This figure does not show the contribution of the first factor, the measured (P50) annual mean wind speed, given that it is two orders of magnitude higher than the rest and would render difficult its interpretation.

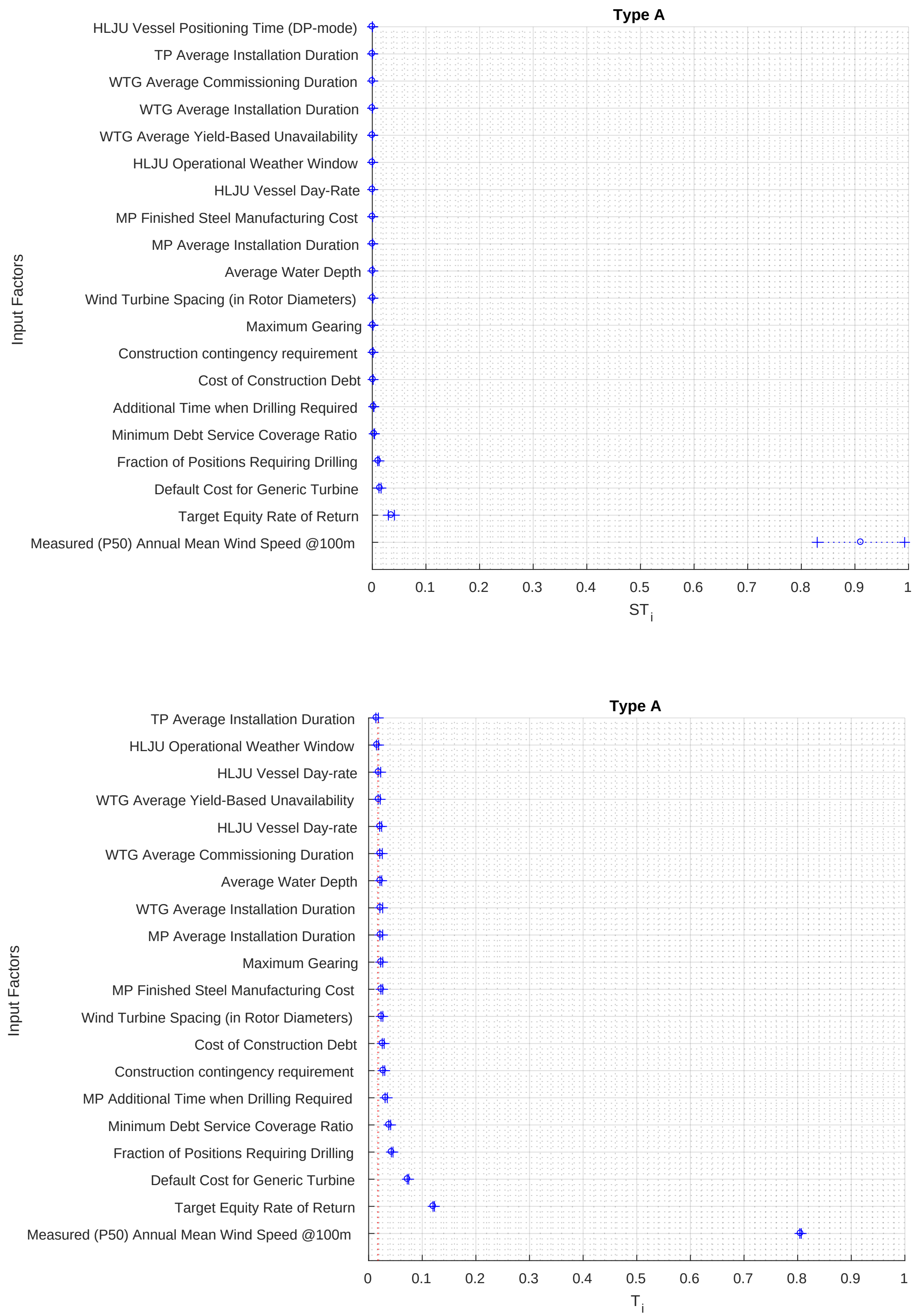
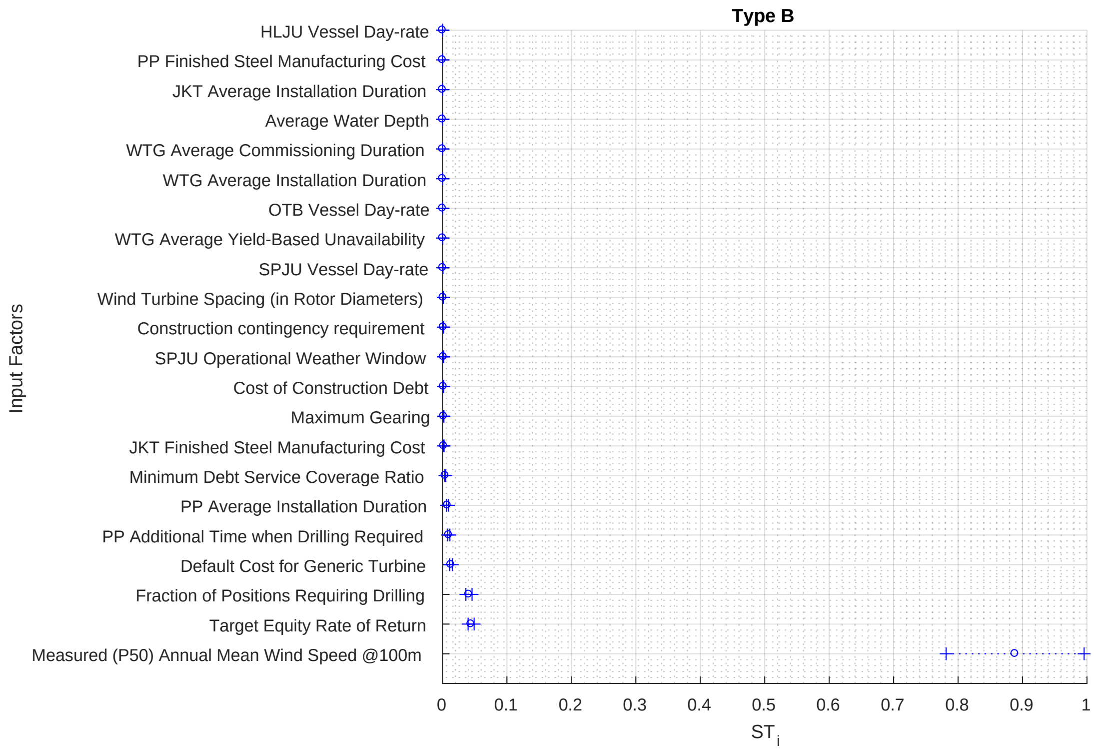


Figure 7: Second stage global sensitivity analysis applied to OWCAT for Type A offshore wind farm



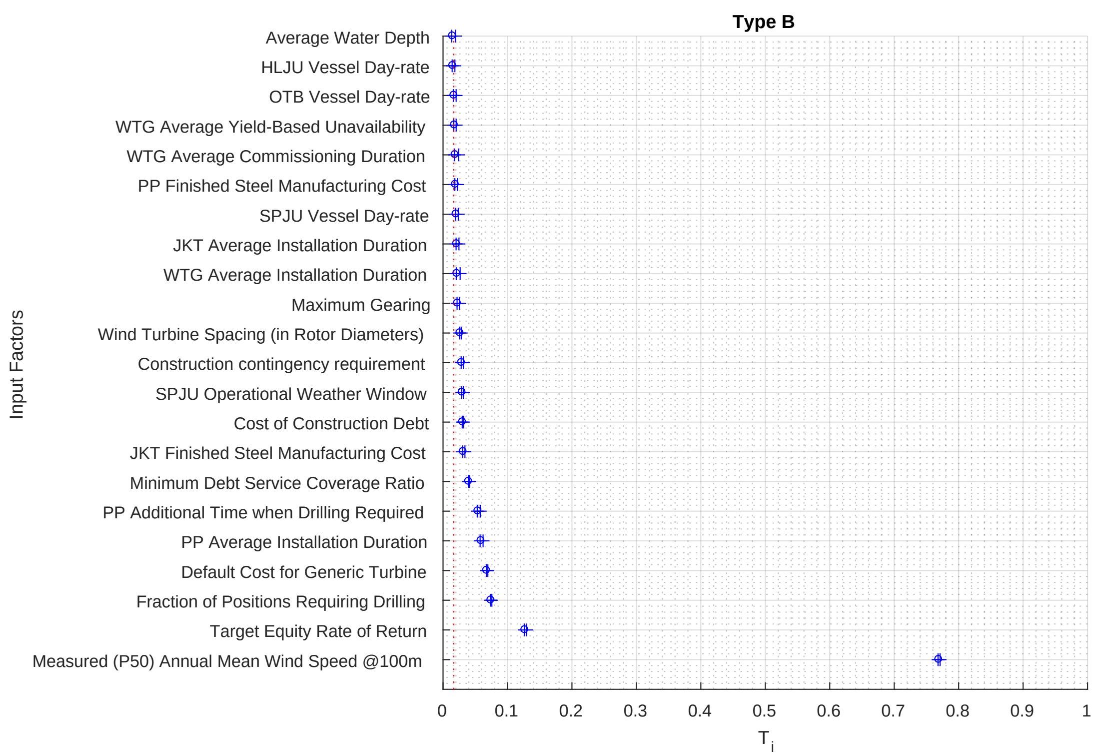


Figure 8: Second stage global sensitivity analysis applied to OWCAT for Type B offshore wind farm

The bottom 5 parameters in Figure 7 and 8 represent the items that contribute the most to the variability of the LCOE, and therefore the paremeters the decision maker should focus on. A side-by-side comparison shows that these 5 parameters for Type A are ranked the same for both the variance-based and PAWN distribution-based methods; these are the measured (P50) annual mean wind speed, the target equity rate of return, the default cost for generic turbine, the fraction of position requiring drilling, the minimum debt service coverage ratio and the additional time when drilling is required. This is similar for Type B, where the difference between the variance-based and PAWN distribution-based methods is reflected in a swap on the fifth and 6th parameter - the additional time when drilling is required for the average installation duration for pinpiles. Further details for each of them are given below:

- Estimated (P50) annual mean wind speed, i.e. the mean wind speed that is expected to be exceeded in 50% of the estimates – the median mean wind speed. Further information on the estimated annual mean wind speed can be found in.[24]
- MARR: the minimum acceptable rate of return the company is willing to accept, given its attitude to risk and opportunity costs. The MARR is typically defined by the company and imposed to be no lower than the IRR of the project. The cost modelling tool imposes a MARR to work out the LCOE. Further information on the financial modelling can be found in the "Formation of the financial module" section of.[24]
- Default costs for generic wind turbine: Generic offshore wind turbine costs expressed as units of currency per kW.
- Fraction of position requiring drilling: This concerns the foundation installation part of the cost modelling tool. Foundations can be either driven or drilled depending on the soil conditions. A distinction needs to be made between Type A and Type B offshore wind farm. Whereas Type A is impacted by the use of monopiles which are highly sensitive to soil conditions, Type B uses jackets which are typically less sensitive.
- Minimum debt service coverage ratio, i.e. the cash flow available for debt service divided by the actual debt service. This metric is typically used in private infrastructure project debt analysis to decide if the project generates enough cash to repay its obligation.
- Additional time when drilling is required:

  The installation time of the monopiles or pinpiles depends upon whether or not drilling is required. The model captures this characteristic by increasing the average installation time by an additional duration. Whereas this parameter models the additional time, the fraction of position requiring drilling depends on the bathymetry of the offshore wind farm.

Table 2 in the Appendix includes further information regarding the 20 selected parameters for Type A and 22 selected parameters for Type B in table 3. The data have been obtained from discussions with practitioners.

7 Conclusions

Global sensitivity analysis for offshore wind cost modelling provides a methodological framework to unlock further cost reductions. The methodological framework allows users to choose global sensitivity analysis techniques for offshore wind techno-economic models. A strategy to interrogate the model by means of the latest global sensitivity analysis techniques has been developed and applied to the offshore wind cost modelling tool.

The results of the global sensitivity analysis highlight the importance of the mean wind speed uncertainty in the design of offshore wind farms. This highlights that the overriding factor to further decreased in costs falling costs is larger turbine sizes. Larger turbines sweep a larger area and, because of their higher hub height, are subject to higher and more consistent wind speeds, increasing their yield and capacity factors. Larger turbines not only increase yield but also reduce offshore wind CAPEX and OPEX, with key impacts on balance of plant and installation costs due to the reduced number of units. Beyond this, sensitivities to input parameters follow a very asymmetric distribution of importance, with few inputs accounting for most of the LCOE output uncertainty and most inputs playing little to no role. Although results for different sites are similar, monopile foundations are more sensitive to water depth than jackets. However, jacket offshore wind farms are very sensitive to pinpile installation times, especially when drilling is required.

In general, the top 6 parameters to consider when building an offshore wind investment business case are: the measured (P50) annual mean wind speed, the target equity rate of return, the default cost for generic turbine, the fraction of position requiring drilling, the minimum debt service coverage ratio and the additional time when drilling is required. The two global sensitivity analysis methods give very similar results in terms of the key drivers to unlock further cost reductions - these top 6 parameters. However, differences in the ranking are observed when looking at the contribution of the second order effects of the rest of the parameters to the variability of the LCOE output uncertainty.

This study is of interest to developers, investors and policy-makers alike seeking to understand which techno-economic parameters are key when building offshore wind investment models.

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9 Appendix

The second stage GSA comprises the following list of input parameters, described by Input Tag, Input Description, Units and Uncertainty Type. The Uncertainty Type represents the probability distribution associated to a given input. $X_i \sim N(\mu, \sigma)$ represents a normal distribution with mean (μ) and relative standard deviation (σ) expressed as a percentage of the mean. $X_i \sim PERT(a, b, c)$ represents a PERT distribution defined by the minimum (a), most likely (b) and maximum (c) values that a variable can take. $X_i \sim U(a, b)$ represents a uniform distribution with the bounds defined by the parameters a and b, which are the minimum and maximum values.

Input Tag	Input Description	Units	Uncertainty Type
$v_{WindMes}$	Measured (P50) Annual Mean Wind Speed @ 100m	[m/s]	$\sim N(9, 10)$
i_{Hurdle}	Target Equity Rate of Return	[%]	$\sim PERT(8, 10, 13)$
$c_{Spec_{WTG}}$	Default Cost for Generic WTG	[2015 €/kWh]	$\sim PERT(1062.5, 1250, 1437.5)$
f_{Drill}	Fraction of Positions Requiring Drilling	[%]	$\sim U(0, 100)$
$DSCR_{min}$	Minimum Debt Service Coverage Ratio	[-]	$\sim PERT(1.19, 1.61, 1.4)$
$h_{Drill_{MP}}$	Additional Time when Drilling Required MP	[h]	$\sim PERT(42, 84, 168)$
$m_{DebtCon}$	Cost of Construction Debt	[bps]	$\sim PERT(255, 300, 345)$
$cont_{Con}$	Construction contingency requirement	[%]	$\sim PERT(10.2, 12, 13.8)$
$f_{DebtMax}$	Maximum Gearing	[%]	$\sim PERT(55.25, 65, 74.75)$
f_{Space}	Wind Turbine Spacing	[# D]	$\sim PERT(5.525, 6.5, 7.475)$
d_{Water}	Average Water Depth	[m]	$\sim PERT(21.25, 28.75, 25)$
$h_{Instal_{MP}}$	Average Installation Duration MP	[h]	$\sim PERT(12, 24, 48)$
$c_{Steel_{MP}}$	Finished Steel Manufacturing Cost MP	[2015 €/t]	$\sim PERT(1700, 2000, 2300)$
$day_{Rate_{HLJU}}$	Vessel Day-Rate HLJU	[£2015/day]	$\sim PERT(127500, 150000, 172500)$
$w_{Op_{HLJU}}$	Operational Weather Window HLJU	[%]	$\sim PERT(63.75, 75, 86.25)$
$f_{Unavail_{WTG}}$	Average Yield-based Unavailability WTG	[%]	$\sim PERT(4.25, 5, 5.75)$
$h_{Instal_{WTG}}$	Average Installation Duration WTG @ 100m	[h]	$\sim PERT(12, 24, 48)$
$h_{Comm_{WTG}}$	Average Commissioning Duration WTG	[h]	$\sim PERT(36, 72, 144)$
$h_{Instal_{TP}}$	Average Installation Duration TP	[h]	$\sim PERT(9, 18, 36)$
$h_{pos_{HLJU}}$	Vessel Positioning Time (DP-mode) HLJU	[h]	$\sim PERT(4.5, 9, 18)$

Table 2: Key drivers for Site Type A in OWCAT when using Monopiles, in order of importance

Input Tag	Input Description	Units	Uncertainty Type
$v_{WindMes}$	Measured (P50) Annual Mean Wind Speed @ 100m	[m/s]	$\sim PERT(9.5, 0.1)$
i_{Hurdle}	Target Equity Rate of Return	[%]	$\sim PERT(8, 10, 13)$
f_{Drill}	Fraction of Positions Requiring Drilling	[%]	$\sim PERT(0, 100)$
$c_{Spec_{WTG}}$	Default Cost for Generic WTG	[2015 €/kWh]	$\sim PERT(1062.5, 1250, 1437.5)$
$h_{Drill_{PP}}$	Additional Time when Drilling Required PP	[h]	$\sim PERT(24, 48, 96)$
$h_{Instal_{PP}}$	Average Installation Duration PP	[h]	$\sim PERT(12, 24, 48)$
$DSCR_{min}$	Minimum Debt Service Coverage Ratio	[-]	$\sim PERT(1.19, 1.4, 1.61)$
$c_{Steel_{JKT}}$	Finished Steel Manufacturing Cost JKT	[2015 €/t]	$\sim PERT(3825, 4500, 5175)$
$f_{DebtMax}$	Maximum Gearing	[%]	$\sim PERT(55.25, 65, 74.75)$
$m_{DebtCon}$	Cost of Construction Debt	[bps]	$\sim PERT(255, 300, 345)$
$w_{Op_{SPJU}}$	Operational Weather Window SPJU	[%]	$\sim PERT(63.75, 75, 86.25)$
$cont_{Con}$	Construction contingency requirement	[%]	$\sim PERT(10.2, 12, 13.8)$
f_{Space}	Wind Turbine Spacing	[# D]	$\sim PERT(5.525, 6.5, 7.475)$
$day_{Rate_{SPJU}}$	Vessel Day-Rate SPJU	[£2015/day]	$\sim PERT(97750, 132250, 115000)$
$f_{Unavail_{WTG}}$	Average Yield-based Unavailability WTG	[%]	$\sim PERT(4.25, 5, 5.75)$
$day_{Rate_{OTB}}$	Vessel Day-Rate OTB	[£2015/day]	$\sim PERT(38250, 51750, 45000)$
$h_{Instal_{WTG}}$	Average Installation Duration WTG @ 100m	[h]	$\sim PERT(12, 24, 48)$
$h_{Comm_{WTG}}$	Average Commissioning Duration WTG	[h]	$\sim PERT(36, 72, 144)$
d_{Water}	Average Water Depth	[m]	$\sim PERT(38.25, 45, 51.75)$
$h_{Instal_{JKT}}$	Average Installation Duration JKT	[h]	$\sim PERT(12, 24, 48)$
$c_{Steel_{PP}}$	Finished Steel Manufacturing Cost PP	[2015 €/t]	$\sim PERT(2125, 2500, 2875)$
$day_{Rate_{HLJU}}$	Vessel Day-Rate HLJU	[£2015/day]	$\sim PERT(127500, 150000, 172500)$

Table 3: Key drivers for Site Type B in OWCAT when using Jackets, in order of importance

Table 4: Review of the different sensitivity analysis methods

SA name	Description	References
One-at-a-time methods (OAT) and Tornado diagrams	Quantify the effect of a change in x_i from a base case to a sensitivity case. Often graphically represented in a Tornado diagram. This SA technique has the following properties: local, quantitative, conditional, moment independent, easy to interpret and implement and stable. However, it neglects interaction effects and is strongly dependent on the chosen point. The computational complexity is $2N+1$,where N is the number of inputs. OATs are widely used in the industry due to its ease of implementation.	[39]
Extended OAT and Tornado diagrams	Generalization of OAT by including interaction effects. Results are still strongly dependent on the chosen point. The computational complexity increases linearly in the number of outputs	[39]
Graphical methods - spider plots and one way SA	Computes the values of the model output while the input varies over their entire range to visually identify the global sensitivity of model outputs to a particular input. Prohibitively expensive for more than a small number of inputs, especially if they have a large range.	[39]
Differentiation-based	Quantifies the rate of change in outputs resulting from small variations in model inputs, calculating local gradients. This is more appropriate for high dimensional models, but interactions are only characterized by the use of expensive second or higher order analysis, and differentiation-based methods can only be applied to continuous inputs.	[19,39]
Screening methods - Morris	Evaluation the model at a limited number of points in the (high-dimensional) input space. The Morris methods has been popular, at the expense of other screening methods such as the supersaturated design and sequential bifurcations due to its completeness .[40] One of the main issues with Morris method is the fact that it does not quantify how much interactions the inputs have.	[39,41–44]
Regression-Correlation	Evaluating a limited number of points in the input space and using these as inputs for a statistical analysis. Can only be applied when the model is at least quasi-linear.	[19]
FAST	The Fourier Amplitude Sensitivity Test uses a multidimensional Fourier transformation of the function of study. In this way, this led to a mono-dimensional Fourier decomposition along a curve exploring the input space. This SA technique has the following properties: global, quantitative, model independent, moment dependent, unconditional, easy to interpret and stable. However, it does not calculate the interaction effects and it is quite complex to implement.	[45,46]
Extended FAST	Extension of FAST to compute the total order effects. The method is also referred as eFAST. Its implementation is complex and it has therefore seen limited use.	[47]
Variance-based	Variance-based methods decompose model output variance in first order and and higher order effects. These SA techniques assume that the variance is a good proxy for uncertainty.	[18,30,33,48]
Entropy Density-based	Measures the divergence between the unconditional and the conditional PDFs by either the Shannon or Kull-back-Leibler entropy. Not easy to implement if calculating empirical pdfs is difficult. In addition, the results are highly dependent on the choice of conditioning values.	[49]
δ Density-based	Considers changes in model output by conditioning values x_i and measuring the area enclosed between the conditional and conditional probability distribution function. Not easy to implement if calculating empirical pdfs is difficult.	[50]
PAWN distribution-based	Considers the changes in model output when fixing a variable x_i, by analysing the distance between the empirical conditional and unconditional cumulative probability distribution functions. Its computational expense is linear in the number of uncertain inputs, so it can be used for high-dimensional models.	[37,51,52]

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