A review of sensitivity analysis practices in wind resource assessment

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Highlights — **Variables used as sensitivity analysis models are identified; evidence of pitfalls in such practices is provided; nonlinear sensitivity analysis models prevail in wind resource assessment; one-at-a-time sensitivity analysis prevails in wind resource assessment; one-at-a-time sensitivity analysis does not apply to nonlinear models;**

Abstract — **A review of sensitivity analysis in wind resource assessment is presented, offering classifications by sensitivity analysis output variable (or model), method, application, country, and software. No review of sensitivity analysis in wind resource assessment is currently available in the literature. The review pool consists of 102 articles with models dealing with statistical and economic aspects of wind resource assessment (goodness-of-fit metrics, wind power, wind energy, the net present value, the payback period, the internal rate of return, the payback period, the levelized cost of energy, capital and operational expenses). Sensitivity analysis studies, where the wind is predicted with weather research and forecasting models, sensitivity analysis of hybrid energy systems with a wind component, and sensitivity analysis of wind turbine fatigue loads, are beyond the scope of this review. This review reveals the lack of collective agreement on the definition of sensitivity analysis in the literature, the dominance of nonlinear models (100%), and the prevalence of one-at-a-time sensitivity analysis method (82%). The review highlights the existing gaps in the field, provides evidence of the common pitfalls, possibly leading to costly misinterpretations of the data at the site and hence to erroneous feasibility assessments. The review urges to rethink how to conduct sensitivity analysis in wind resource assessment. It also includes comparison of one-at-a-time sensitivity analysis and global sensitivity analysis for a linear and nonlinear models.**

Word count — **23100**

Keywords — **wind energy, wind resource assessment, sensitivity analysis, global sensitivity analysis, uncertainty analysis**

Contents

Nomenclature

μ_i	The mean of elementary effect of Morris [1]
μ_i^*	The improved sensitivity measure of [2] based on the Morris method [1]
P_{WT}	Wind turbine rating
P_{WF}	Installed windfarm capacity
S_i	Sobol first-order sensitivity indices [3][4]
T_i	Sobol total effect sensitivity indices [3][4]
V_{T_i}	a variance based on the total effect for a factor X_i
V_i	a variance based on the first-order effect for a factor X_i
$X_{\sim i}$	$N \times (k-1)$ matrix of all factors but X_i
X_i	Generic sensitivity analysis input variables
WD	Water depth
D	Distance to shore
d_i	Elementary effect of Morris [1]
σ_i	The standard deviation of elementary effects of Morris [1]
A	$N \times k$ sample matrix of inputsIVs used
AEP	Annual energy production
B	Benefit in cost-benefit analysis
C	Cost in cost-benefit analysis
$CAPEX$	Capital expense
E	Energy
h_0	Roughness length
H	Wind turbine height
$LCOE$	Levelized cost of energy
$OPEX$	Operational expense
A	Cross sectional area of a wind turbine rotor
P	Power
N	Sample size
R	Discount rate
T	Time
W	Wind speed
Y	Function, response, model, output
Λ	Scale parameter of the two-parameter Weibull distribution
P	Air density
c	Shape parameter of the two-parameter Weibull distribution
k	Number of inputs

List of abbreviations

AEP	Annual energy production
ANN	Artificial neural network
ANOVA	Analysis of variance
ARIMA	Auto-regressive integrated moving average
CAPEX	Capital expenditure
CBA	Cost-benefit analysis
CDF	Cumulative distribution function
CF	Capacity factor
CS	Case study
DOE	Design of experiment
DM	Distribution model
DR	Discount rate
DWP	Dispersed wind power
D&C	Costs of development and consenting of a wind project
eFAST	Extended Fourier sensitivity analysis test
FAST	Fourier amplitude sensitivity test
FC	Foundation costs
FIT	Feed-in tariff
FOFFWF	Floating offshore wind farm
FS	Feasibility study
FUSED-Wind	Framework for unified systems engineering and design of wind plants [5]
GIS	Geographical information system
GOF	Goodness-of-fit
GOFM	Goodness-of-fit metric
GSA	Global sensitivity analysis
GSAR	Global sensitivity analysis result
HES	Hybrid energy system
HH	Hub height
IR	Interest rate
IRR	Internal rate of return
IV	Input variable
JUV	Jack up vessel
KS	Kolmogorov-Smirnov statistic
LCOE	Levelized cost of energy
LM	Linear model
LSA	Local sensitivity analysis
MAE	Mean absolute error
MC	Monte Carlo
MLP	Multi-layer perceptron
MSE	Mean standard error
MTTF	Mean time to failure
NG	Natural gas
nonLM	Nonlinear model
NPV	Net present value
NREL	National Renewable Energy Laboratory
O&M	Operation and maintenance
OAT	One-at-a-time
OATSA	One-at-a-time sensitivity analysis

OATSAR	One-at-a-time sensitivity analysis result
OFFWF	Offshore wind farm
ONWF	Onshore wind farm
OPEX	Operational expenditure
OV	Output variable
PAWN	Distribution based method of global sensitivity analysis [6]
PC	Power curve
PDF	Probability density function
PO	Power output
PP	Payback period
PPA	Power purchase agreement
P&A	Production and aquisition
QMC	Quasi-Monte Carlo
RA	Risk analysis
RC	Repowering cost
R&D	Research and development
RL	Roughness length
RMSE	Root mean square error
SA	SA
SAFE	Sensitivity analysis for everyone [7]
SAIV	Sensitivity analysis input variable
SAOV	Sensitivity analysis output variable
SAR	Sensitivity analysis result
SD	Standard deviation
SI	Sensitivity index
SP	Superposition principle
SR	Surface roughness
SWD	System of wind speed distributions
TD	Tornado diagram
TEA	Techno-economic assessment
TS	Time series
UA	Uncertainty analysis
UNFCCC	United Nations Framework Convention on Climate Change
UQ	Uncertainty quantification
W2	The two-parameter Weibull distribution
WE	Wind energy
WF	Wind farm
WFPO	Wind farm power output
WM	Wake model
WP	Wind power
WRA	Wind resource assessment
WRF	Weather research and forecasting
WRFM	Weather research and forecasting model
WS	Wind speed
WSC	Wind shear coefficient
WSTS	Wind speed time series
WT	Wind turbine
WTFL	Wind turbine fatigue load

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1 Introduction

Uncertainty is inherent to the scientific method [4]. Sensitivity analysis (SA) is the study of how the uncertainty in the output of a mathematical model, system or output variable (OV)[1] can be allocated to different sources of uncertainty in its input variables (IV)[2] [4]. Uncertainty analysis (UA) is a neighbouring practice. UA focuses on the uncertainty quantification (UQ), while SA attributes parts of it to the inputs. The questions UA and SA address are different. UA answers the question of *how* uncertain the output is, while SA - *where* the uncertainty originates[3]. SA means to establish a ranking of inputs. One-at-a-time (OAT) SA (OATSA)[4] commonly quantifies the impact on the model of based on a p% increase and decrease in each input.

Saltelli et al. [8] called for SA to be promoted as an independent discipline due to its unused potential. Although, global SA (GSA) is already a part of a number of international guidelines for impact assessment [9][10] and disciplinary journals , its uptake is still "*in its infancy*" [11].The term SA is vastly stereotyped as OATSA [12], even across the scientific community. This review is conceptualized around this stereotype. SA in WRA is no exception. Tsvetkova et al. [13] stated that OATSA is typical for WRA (evidence required) and voiced concern about the validity of OATSA for nonlinear models (nonLMs) in WRA. However, are nonLMs typical for WRA? The review intends to provide evidence of SA pitfalls present in WRA [13], OATSA and nonLMs prevalence in WRA. Reviews of UA in WRA exist in the literature, e.g. [14], but a review of SA in WRA does not. A recent review of Azavedo et al. [15] identified the main impact factors on economical feasibility of wind projects and suggested performing SA of NPV, IRR, PP based on the identified inputs. There is a growing interest in SA in relation to WRA.

The main contributions of this paper are: (1) providing such a review, (2) providing classifications of SA studies based on method, location and software, (3) identifying the commonly used outputs (SA models) in WRA, (4) locating gaps in published research (Section 10), (5) explaining the specific application in WRA with its advantages and shortcomings (Section 8) (6) comparing OATSA and GSA for a cost model commonly used in WRA. The goals of this review are to (1) shed light on the inconsistencies present in the use of SA in the field, (2) encourage the use of UA/SA in WRA studies, and (3) promote the use of appropriate SA methods for the models used in WRA, so that policy implications were made on credible results.

The review is organized in ten sections: 1 Introduction, 2 Sensitivity analysis models, 3 Sensitivity analysis methods, 4 Offshore vs. onshore, 5 Geography, 6 Software, 7 Evolution, 8 Specifics of application, 9 Critical synthesis, and 10 Conclusion and outlook. The most detailed review classification is based on the SA model and is given in Section 2. The scope of this review is limited to SA of goodness-of-fit metrics (GOFMs), wind power (WP), wind energy (WE), net present value (NPV), internal rate of return (IRR), payback period (PP), and levelized cost of energy (LCOE). There are four significant clusters of ongoing research in neighbouring topics

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[1] The terms system, mathematical model, model, SA output, output, output variable, function, and response are used interchangeably throughout this article, moreover as far as SA is concerned the OV can be a black-box, when nothing is known about the underlying relationship between the inputs and the output.

[2] The terms input and input variable are used interchangeably throughout the article.

[3] Other questions SA addresses include: which inputs are most and least influential on the model, how a certain level of risk in the model can be achieved [1].

[4] OATSA is a variation of one input at a time while keeping the rest fixed, and looking at the response in the OV.

outside the review's scope: (1) SA of wind turbine fatigue loads (WTFLs), (2) SA of weather research and forecasting models (WRFM's), (3) SA of hybrid energy systems (HES's) with a wind component, and (4) SA used in wind farm (WF) layout optimization [16]. SA of WTFL tends to use universal GSA, and of WRFMs – OATSA [13]. SA of HES's mostly employs OATSA [17]. WRFM's predict the WS (often with WP or WE), OATSA of WRFM's can be justified by the computational burden and many SAIV typical for such models [13].

2 Sensitivity analysis models

Section 2.1 discusses model linearity and explains why it is crucial when choosing a SA method. Section 2.2 walks the reader through the typical process in WRA, discusses which WRA variables act as SAOVs. Section 2.3 reviews the economic variables found to be a SAOV.

2.1 Linear models vs. nonlinear models

In mathematics, a linear system is a system satisfying the superposition principle (SP) [18] - that for all linear systems, the response caused by multiple stimuli, is the sum of individual responses [19]. The essence of the SP is in additivity ((1)) and homogeneity ((2)). A linear function *Y* is one satisfying the SP. In SA, LMs exhibit behaviour described in (3) [4].

$$Additivity: F(X_1 + X_2) = F(X_1) + F(X_2) \tag{1}$$

$$\textit{Homogeneity:}\ F(aX) = aF(X) \tag{2}$$

$$Y = b_0 + \sum_{r=1}^{k} b_r X_i = b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_k X_k \tag{3}$$

For a model to be linear, all the relationships between inputs X_i and *Y* should be linear ((4)). Vice versa, to classify a model as nonlinear, it is sufficient to show that at least one relationship between X_i and *Y* is nonlinear.

$$Linear\ relationship: Y \sim X_i \tag{4}$$

$$Nonlinear\ relationship: Y \sim 1/X_i, Y \sim {X_i}^n, Y \sim \ln X_i, Y \sim e^{X_i} \ldots \tag{5}$$

The local or OAT approach is limited to LMs [20][21][22], while GSA is a universal tool applicable to *any* model.

2.2 The statistics behind wind resource assessment

WRA starts with statistically modelling the WS. WS time series (WSTS) is fitted with a distribution model (DM), most commonly with the two-parameter Weibull (W2) distribution (1) [23][24][25][26][27], although other DMs are possible [28][27][29][30][31].

$$f(w) = \frac{c}{\lambda}\left(\frac{w}{\lambda}\right)^{c-1} e^{-\left(\frac{w}{\lambda}\right)^{c}}, \tag{6}$$

2.2.1 Goodness-of-fit metrics

Then the goodness-of-fit (GOF) is evaluated by calculating GOFMs characterizing the fit between the collected WSTS and a DM. Ouarda et al. [30] and Vargas et al. [32] reviewed GOFMs used in WRA (summarized in *Table 1*). All the studies mentioned in this section used OATSA, despite the eye-catching nonlinearity of GOFMs.

Table 1: Goodness-of-fit metrics used in WRA [30][32]

GOFM	Formula	Comment
Log-likelihood	$\ln L = \ln \sum_{i=0}^{N} f(w_i)$	w_i is the WSTS
Akaike information criterion	$AIC = -2 \ln L + 2k$	k is the number of parameters of a distribution
Bayesian information criterion	$BIC = -2 \ln L + k \ln N$	N is the WS sample size
Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=0}^{n} (w_i - v_i)^2}{\sum_{i=0}^{n} (w_i - v_{ave})^2}$	
Coefficient of determination giving the degree of fit between the theoretical cumulative distribution function and the empirical cumulative probabilities of WS data	${R^2}_{PP} = 1 - \frac{\sum_{i=0}^{n} (F_i - \widehat{F_i})^2}{\sum_{i=0}^{n} (F_i - \bar{F})^2}$	
Coefficient of determination giving the degree of fit between the theoretical WS quantiles and the WS data	${R^2}_{QQ} = 1 - \frac{\sum_{i=0}^{n} (w_i - \widehat{w_i})^2}{\sum_{i=0}^{n} (w_i - \bar{w})^2}$	
The adjusted coefficient of determination	${R^2}_a = 1 - (1 - R^2) \frac{\mathrm{N} - 1}{N - d}$	N is the WS sample size, and d is the number of parameters in a statistical model
Root mean square error, RMSE	$RMSE = \sqrt{\frac{\sum_{i=0}^{n} (w_i - \widehat{w_i})^2}{n}}$	
Chi-square test statistic	$\chi^2 = \frac{\sum_{i=0}^{n} (O_i - E_i)^2}{\sum_{i=0}^{n} E_i}$	
Kolmogorov-Smirnov statistic (KS)	$\mathrm{D} = \max_{1 \le i \le n} F_i - \widehat{F_i}$	
Anderson-Darling statistic	$A = -n - \sum_{i=1}^{n} \frac{2i-1}{n} \left(\ln\left(\widehat{F_i}\right) + \ln\left(1 + \widehat{F_{n-i+1}}\right)\right)$	

Mean absolute error (MAE)	$$MAE = \sum_{i=1}^{n} \lvert w_i - \widehat{w_i} \rvert$$	
Mean absolute percentage error, MAPE	$$MAPE = \frac{1}{n} \sum_{i=0}^{n} \frac{w_i - \widehat{w_i}}{w_i}$$	
Standard deviation	$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=0}^{n} (w_i - \overline{w_i})^2}$$	

Only two studies on SA of GOFMs of some distributions to fit WSTS were found [33][34]. Alavi et al. [33] pursued SA of four DMs (lognormal, gamma, Rayleigh, W2) with actual and truncated WSTS with an Iranian case study (CS). They pointed to the lack of SA studies of GOFMs to the accuracy of measured data. OATSA of GOFMs (such as MSE, normalized MSE, normalized RMSE, MAE, RMSE, mean absolute relative error, coefficient of determination, and coefficient of efficiency) to the change in the accuracy of WS at five locations was conducted. GOF of the original and truncated to integer values WSTS were compared, showing that the lognormal distribution is best-fit to the original WSTS, while W2 - to the truncated WSTS [33].

Jung et al. [34] investigated the effect of WSTS quality on ten GOFMs for a system of WS distributions (SWD) comprised of the Burr-Generalized Extreme Value, Kappa, and Wakeby distributions. The GOFMs were KS, ${R^2}_{PP}$, ${R^2}_{QQ}$, $RMSE_{PP}$, $RMSE_{QQ}$, MAE_{PP}, MAE_{QQ}, relative error of the mean of the cubes of WS, annual energy production (AEP) error, and percentage of AEP error. WSTS from 187 German locations were used. Jung et al. [34] emphasized the lack of results in the literature for fitting a distribution to poor quality WSTS. The percentage of missing data, the data resolution, and the temporal resolution were altered, and the AEP was calculated. The goal was to evaluate the robustness of SWD against measurement errors, missing values, and low temporal resolution. SWD was found robust against all the SAIVs, despite the application of OATSA [34].

2.2.2 Wind power

Once WS data are fitted to a DM, WP can be assessed. Both GSA [35][36][37][38][39][40][41][42] (47%) and OATSA [43][44][45][46][47][48][49][50](53%) were conducted for WP. Weekes et al. [35] performed GSA of WP density of a small-scale onshore WT in the UK with the Sobol method using GUI-HDMR [51]. The SAIVs were regional displacement height, roughness length (RL), blending height, and W2 shape factor. GSA results (GSARs) differed across ten locations. On average W2 shape was top-ranked, explaining 37% in WP variance. McKay et al. [36] and Tong et al. [37] used extended Fourier amplitude sensitivity testing (eFAST) to study the effects of wake models (WMs) on WP. SAIVs in [36] were yaw angle, rotor speed, blade pitch angle, WS, ambient temperature, main bearing temperature, WS standard deviation (SD), and yaw angle SD, in [37] - WS, ambient turbulence, land area per MW installed, land aspect ratio, and nameplate capacity. The GSARs accounting for wake effects in [36] ranked WS and WS SD as the top contributing to WP variance. Tong et al. [37] found that (1) when the WS is less than the WT rated WS, its effect is dominant regardless of the WM used, (2) the relative importance of each IV is less sensitive to the choice of WM for WFs with optimized layouts. Finally, Ulker et al.

[38] conducted a GSA of both onshore WT and WF power output (PO) for WT micro-siting. The SAIVs was the W2 parameters, power turbulence intensity, power wind shear, and operational pitch control. SARs in [38] ranked the W2 scale at the top - responsible for 63-77% of WT and 69-83% of WF PO variance. WT PO in [38] was calculated as (7). Wake effects influence on AEP variance was found negligible in [52] and significant in [53]. Also, the use of very accurate WMs was found overstated in [52].

A recent study by Carta et al. [39] proposed a GSA method tailored to wind farm power output (WFPO) estimation models. Moreover, in [39] Sobol indices were compared to Shapley effects [54] and regular vine copula was used to simulate the dependency among the inputs. The model used in the CS of [39] for WFPO proposed by Diaz et al. [55] was fed with sixteen meteorological and six operational inputs. The data used in the CS of [39] is historical operational data of the Gorona del Viento wind-hydro power plant (El Hierro-Canary Islands-Spain). Carta et al. [39] found that the WS, active power set-point and turbulence intensity variables accounted for 98.58% of the variance in the WFPO model, while the wind direction, nacelle orientation and air density – for only 1.42%. They also found that Shapley effects overcame the difficulty of the presence of correlation of inputs to the WFPO model as compared to the Sobol indices that operate based on the assumption that the inputs are statistically independent.

$$P_{ave} = \int_0^\infty \mathrm{P(w)}\, \pi_w(w)\, dw = \int_0^\infty \mathrm{P(w)}\, \frac{c}{\lambda}\left(\frac{w}{\lambda}\right)^{c-1} e^{-\left(\frac{w}{\lambda}\right)^c} dw, \tag{7}$$

Where the WT power curve (PC) is $\mathrm{P(w)}$, $\pi_w(w)$ is the WS probability distribution function (PDF), c and λ are the W2 parameters.

Aghbalou et al. [42] conducted a probabilistic assessment approach for WT-site matching with a GSA of performance function and probability of operating based for a CS ot two sites in Morocco. The performance function was defined as the difference between electrical power and critical power. The WS and rated WS show most influence on the performance of a WT.

Much risk in WRA is associated with the volatile nature of the wind. Naturally, the WS or its DM parameters often serve as SAIVs. The relationship between the WS and WP is known to be cubical (8) [25], so whenever the WS or its DM parameters are present among SAOVs, OAT is not acceptable. Numerous attempts at quantifying the uncertainty in WP associated with the WS were made [35]-[45][44], some - with OATSA [43][45][44]. He et al. [45] sharply observed that all relationships between SAIVs (WS threshold, slope threshold, elevation threshold, and bathymetry threshold) and the SAOV were nonlinear, but used OATSA nonetheless.

$$P = \frac{1}{2} C_p \rho A\, w^3, \tag{8}$$

Where C_p is the coefficient of performance (that depends on the yaw angle, rotor speed, and blade pitch angle), ρ is the air density (inversely proportional to the mean bearing temperature), A is the cross-sectional area of the rotor and w is the WS.

Eisa et al. [44] studied sensitivity of mechanical power with the model of a type-3 DFAG/DFIG wind turbine generator with close attention to behaviour at higher wind speeds with the pitch control activated. The goal was to understand how fast the pith angle needs to respond to the WS change[44]. Although the study focus was on SA, Eisa et al. [44] studied "*sensitivity of the state variables to the parameters by analyzing the effect of changing one parameter while fixing the others*" [44]. Along with the WS, WT pitch control parameters and grid characteristics served as inputs to SA.

Two studies on OATSA of WP [45][46] used GIS tools. He et al. [45] assessed where, when and how much wind is available in China by using ten years of hourly WSTS for two hundred Chinese sites. Nguyen [46] assessed WE potential in Vietnam and reasoned about the development status and future implications. Nguyen [46] claimed that wind potential primarily depends on the assumed discount rate (DR) and specific investment cost. The SA objective in [46] was to provide policymakers with more accurate potential assessment, but research questions were unclear, and no ranking was established.

Kubik et al. [47] compared the log law ((9)) and the power law ((10)) to translate ground WS to hub height (HH) WS with OATSA of WP output to surface roughness (SR) and wind shear coefficient (WSC) for West Freugh, Scotland. As the names and (9)-(10) suggest, the research question calls for GSA due to nonlinearity, but instead, OATSA was used.

$$w(h) = \frac{w_*}{k}\ln(\frac{h}{h_0}), \tag{9}$$

$$w_2 = w_1\left(\frac{h_2}{h_1}\right)^{\alpha}, \alpha = \ln(w_2) - \ln(w_1))/(ln(h_2) - \ln(h_1)), \tag{10}$$

Where h_0 is RL and α is the WSC.

Nedjari et al. [48] studied the wind potential of seventy-four coastal Algerian locations, identified the optimal windy sites, and evaluated wind power's sensitivity (OATSA) to the data time interval. WP density was calculated with different ten-year intervals.

Two recent studies used SA of WT power for PC modelling. A recent study by Saint-Drenan et al. [49], included a parametric model for wind turbine power curves that incorporated environmental conditions. It included a "*univariate*" SA of qualitative nature (OATSA) of the power curve with respect to rotor diameter, nominal power, cut-in and cut-out speed, minimum and maximum rotation speed. Rotor diameter and nominal power are reported to have most impact on the power curve, yet "*their level of uncertainty is negligible as they both are design parameters and most manufacturers mention them directly in the name of the turbine*" [49]. Gonzalez et al. [56] explored using high-frequency SCADA data for WT performance monitoring and found it highly beneficial for this purpose. Sensitivity of power curve models to site specific conditions, seasonality, input relevance and sampling rate was studied with an interesting angle to SA.

Two groups of researchers considered uncertainties in aeroelastic blade models. Kumar et al. [40] studied GSA of model uncertainty in aeroelastic blade element momentum models for WT output with the Sobol method by the means of UQLab [57] tool. The GSA results showed "*the importance of the lift coefficient, especially for the axial force prediction"* [40].The study of Murcia et al. [41] on uncertainty propagation through an aeroelastic blade model using polynomial surrogates included GSA of WTPO, inter alia.

Finally, Haces-Fernandes et al. [50] recently showed improvement of WFPO with selected turbine deactivation, and OATSA of WFPO with regard to turbine rotor diameter was part of the study. The new deactivation concept offered larger PO improvement for WFs with larger turbines installed [50].

2.2.3 Wind energy

Energy is power in a given time, so the nonlinearity concern holds. Yet OATSA of wind energy (WE) [58][59][60][61][62][63][64][65][66] (71%) is more common than GSA [13][52][53][67] (29%). Zhou et al. [58] and Hoogwijk et al. [59] conducted OATSA of global onshore WE potential and generation costs. The SAIVs in [58] were WS, SR, HH, turbine density, land suitability, turbine cost, finance rate, and transmission cost, and WS was found most influential. Zhou et al. [58] used nonlinear (11) to calculate global onshore wind potential. A "*one-factor*" SA [59] was referred to as *"not complex as most relationships are linear"* [59].

$$E_a = f \sum_{i=1}^{8760} \eta_1 \eta_2 \left(\frac{A\delta}{1.5}\right) P_i \quad (11)$$

Where *f* denotes land suitability factor, *A* is the area of each grid cell, η_1 is the availability factor, η_2 is the array efficiency, δ is turbine density, P_i is the hourly WP output that depends on the HH and the RL.

SA of WE is frequent in techno-economic assessments (TEAs). A TEA and UQ of a Finnish onshore WF (ONWF) [60] included OATSA of deterministic and stochastic models of AEP and NPV. A TEA of a real WF repowering experience in Malpica, Spain [61] based on [60] included OATSA (+/-5% of the baseline scenario) of AEP, present value costs, cost of energy, NPV, IRR, PP, and minimum spot price. Inputs to SA of AEP in [61] were W2 parameters, air density and WT power curve, Weibull scale was found most influential on AEP. Khalid et al. Another TEA [62] included OATSA of a hypothetical WF in Pakistan with RETScreen [68]. The SAIVs were initial project cost, electricity export rate, electricity price, escalation rate, debt interest rate (IR), capacity factor (CF), emission reduction income. The SAOVs were net energy produced, generation cost and NPV. The SARs were presented as a plot of NPV depending on the CF. No ranking of inputs was established, and instead, conclusions about the strong dependency were made [62]. A TEA of onshore wind on the Canary Islands [63] implemented OATSA of AEP and LCOE. The singe SAIV was HH. Although SA is meant to establish an input ranking, the analysis was nevertheless referred to as SA [63]. The results showed that for the mountainous islands, no pattern could be established, but in the case of flat islands, the highest HH of 100 m correlated with lower generation cost [63]. Also, Tautz-Weinert et al. [64] performed "*what-if*" SA (OATSA) of an ONWF maintenance decision with performance and revenue analyses. The SAOV was normalized energy production, and SAIVs were optimization delay, additional downtime, shifting of the intervention icing, wind direction, country, taxed revenue, and subsidy. Bistline et al. [65] studied the economic drivers of wind and solar penetration in the US with OATSA of future WE share. The SAIVs were investment costs, natural gas (NG) price, the potential for new inter-regional transmission, availability of low-cost energy storage, and CO2 policy. It was found that "*no single factor unilaterally determines wind and solar deployment*" [65], this statement alone calls for GSA with SAIVs varying simultaneously in contrast to OATSA. The Sobol method was used to account for the WE model nonlinearity [13][52][53][67]. Tsvetkova et al. [13] and Richter et al. [52] applied quasi-Monte Carlo (QMC) technique in GSA in WRA and discussed the related sampling [13][52] and computation problems at length [52]. A non-specific turbine CS on UAE was conducted in [13], and an assessment of four offshore WFs (OFFWFs) - in [52]. SAOV was AEP [13][52], and NPV, IRR, LCOE [52]. The SAIVs in [13] were air density, turbine availability, electric losses, and the W2 parameters, in [52] - WS, wake effect, PC, SR, plant performance, capital cost, O&M cost, DR, and energy price. Air density was found to be most influential in [13], accounting for 94% of AEP variance, WS and PC - in [52] accounting for 80% and 3-9%.

Dykes et al. [53] applied a systems engineering approach to WT key design parameters by using the Sobol, correlation and scatterplot methods to evaluate a US ONWF performance. GSA studies of AEP were conducted with NREL WISDEM [69]. Rotor diameter and WT rated power were found most influential on AEP [53]. Bossavy et al. [67] conducted a GSA of the technical potential GIS assessment of onshore wind and solar technologies. They discovered that parameters related to availability are more influential rather than those related to technology. Sensitivity indices for energy production in Brittany and Provence-Alpes-Cote d'Azur were calculated. The inputs were CF increase ratio from the use of new wind technology, the proportion of fresh wind installed capacity, a parameter indicating whether or not protected natural areas are constraints to WP capacity implantation, and a parameter indicating whether or not protected natural areas are constraints to the wind and solar power capacity implantation. Among other inputs, there was maximum altitude for plant installation, maximum altitude gradient for plant installation, minimum CF suitable for plant installation, and installed capacity by the surface unit at power plant scale. The relative influence of the parameters involved in defining surface availability was estimated at 65-75%.

2.3 The economics of wind resource assessment

The economics of WRA is expressed with cost-benefit analysis (CBA) characterizing a project by NPV, IRR, PP, LCOE, all using AEP in their definition, hence here too the nonlinearity concern persists. Moreover, Harenberg et al. [20] showed that only GSA accounts for nonlinearities and variable interactions and that both are present in economic models.

2.3.1 Net present value

Despite the various nonlinearities among frequent IVs to SA of NPV (WS, DR, lifetime), GSA is rarely used – a single study [52] of the twenty seven reviewed (4%). All studies calculated NPV as:

$$NPV = \sum_{i=0}^{N} \frac{B - C}{(1+r)^i} = \sum_{i=0}^{N} \frac{AEP_i\, FIT - CAPEX_i - OPEX_i}{(1+r)^i}, \tag{12}$$

Where B is the benefit (depends on AEP), C is the cost, i is the time (usually a year), N is the project lifetime, and r is the DR.

One common input in SA of NPV is the DR [52][70][71][72][73][74][75][76][77], the only GSA among these was [52]. (12) shows the nonlinear relationship between the DR and NPV. Nordman [70] performed WRA in Kenya with OATSA of NPV with the initial cost, debt IR, DR, WS, and electricity price as SAIVs. With SARs presented in a table, the conclusion consisted of a determined threshold WS value necessary for a positive NPV [70]. Kongham et al. [71] formulated the investment strategy as a mixed-integer programming problem with the constraints specified as intervals and the NPV as the objective. After finding an optimum solution, OATSA was performed to test the effects of DR, electricity rate, O&M cost, and lifetime on NPV. Higher DR and O&M costs were found to yield higher generation cost [71]. Lozano-Minguez et al. [72] performed multi-criteria assessment of different OFFWT support structures (monopole, tripod and jacket) with OATSA of NPV. The varied parameter was the DR. The SAR was that a DR increase yields NPV decrease [72]. Alonzo et al. [77] quantified the uncertainty of the NPV of virtual onshore and offshore windfarms in France, Germany and Denmark and evaluated the cost of support mechanisms needed to guarantee their profitability under present and future climate. Their study included OATSA of NPV based on DR as "*DR is a parameter that strongly impacts the NPV and as a consequence the profitability of an asset*" [77].

OATSA of NPV conducted in TEAs [60][61][78][79] studied onshore [60][61][78] and offshore [79] wind applications. Afanasyeva et al. [60] pursued technical, economic and uncertainty modelling of a Finnish ONWF with OATSA of a deterministic and stochastic model of AEP and NPV. The SARs were presented in a so-called tornado diagram (TD), commonly used for presenting OATSA results (OATSARs). A TD (Figure 7) shows the importance of inputs for SAOV according to the percent change in SAOV compared to the defined baseline scenario. Afanasyeva et al. [60] report that high impact on NPV has electricity price and O&M cost, while average WS, PC and IR have a common effect. The effect of air density and wake effect was reported insignificant. [61] included OATSA of NPV with SAIVs of AEP, spot energy price, electricity generation tax, general company expenses, WT O&M costs, electrical infrastructure O&M cost, inflation rate, ONWF depreciation, profit tax rate, risk-free rate, debt risk premium, country risk premium, levered beta, and market premium. NPV was found most sensitive to the SP [minimum spot price], the inflation rate, the AEP and the depreciation rate [61]. Hadi et al. [78] performed a preliminary FS for Al-Shehabi, Iraq, which included OATSA of NPV, IRR, and PP with the use of RETScreen [68]. The most influential factors on NPV, IRR and PP were found to be initial investment, electricity export rate, and DR [78]. Ali et al. [79] conducted a TEA of WE potential at three locations in South Korea using long-term WSTS with different HH's.

OATSA of the NPV of onshore applications in Serbia [75] was performed with Oracle Crystall Ball [80], in Myanmar [73] with RETScreen [68], and in Indonesia [81] with @RISK [82]. No ranking of IVs was established with RETScreen [68]. Instead, the change in NPV triggered by the difference in the inputs was reported [73]. Loncar et al. [75] varied CF, risk-adjusted DR, regular price escalation, corporate income tax, specific investment costs, the inflation rate in Euro-zone, specific O&M costs, operational expenditure (OPEX), capital expenditure (CAPEX), and DR and found CF most influential on NPV. Ismail et al. [81] conducted an economic feasibility study (FS) of an ONWF in the coastal South Purworejo. The SAIVs were equity portion, capital investment cost, and O&M cost. The capital investment cost and O&M cost were found influential on NPV [75].

OATSA of the NPV of onshore wind applications in Thailand was found in [76][83][84] and Brazil in [85][86][87]. SAIVs in [76] were WS, DR, tax, salvage value, in [83] - AEP, cost of the turbine, sale of electricity, crude oil price, and inflation rate, in [84] - AEP, project costs, and average tariff,. WS caused the most variance of NPV in [76], AEP - in [83] (similar finding in [88]), and no ranking was established in [84]. WRA and comparative economic assessment using AMOS data of a 30 MW WF in Korea included OATSA of NPV and IRR [84]. The inputs were AEP, renewable energy certificate price, CAPEX, OPEX, and system marginal price. NPV was found most sensitive to AEP and least vulnerable to OPEX [84]. Onshore WP economic feasibility under uncertainty in Brazil was studied in [85]. The SAOV was NPV of an ONWF. The methods of SA used were OATSA, and a novel by using an artificial neural network (ANN). The SAIVs were WS, investment, and energy tariff, while the other parameters were fixed at their baseline values. The SARs were presented as a TD and in a bar plot. TD summarized the OATSARs and bar chart consisted of relative importance (RI) measures for ANN SARs. WS (56%), energy tariff (27%) and the investment amount (16%) were found most relevant factors based on the ANN SARs [85]. WP FS under uncertainty in Brazilian electricity market was conducted in [86]. NPV of WP plant was calculated given a set of assumptions. MC was used for UA and OAT for – SA. IVs to UA/SA were average WS, energy price, investment, O&M, losses in transition lines, insurance, and CO2 ton average price in the European market, emission factor, and leasing, administrative expenses, transmission wheeling charges, annual economic benefit, and ONS/CCEE tax. The SARs were presented as linear plots of NPV (percentage of change to baseline). WS, energy prices, and investment costs were found most significant. Using ANN in SA of NPV of microgeneration of wind energy for small businesses in Brazil is continued by Lacerda et al. [87]. Three states were chosen for feasibility analysis - Rio Grande do Norte, Rio Grande do Sul, and Minas Gerais – with MC UA and ANN based SA. A multi-level perceptron (MLP) was trained with Statistica[89] as proposed by Chakrabarty et al. [90] for economic viability of biogas and green self-employment opportunities. A MLP produces synoptic weights are used for calculation of relative importance that is in turn used as a sensitivity measure on NPV of the project. Most impact on NPV had WS, investment, third party capital, tariff energy, and depreciation [87].

A few recently published studies follow the evident trend of using OAT as SA method of NPV of onshore wind applications [91][92]. The first one studied onshore wind farm siting prioritization based on investment profitability for Greece by Sakka et al. [91]. It included OATSA of NPV and IRR with respect to variance in detailed CAPEX and OPEX costs for a cases study of Lemnos. O&M costs were found most influential on both metrics. Also, Ammizud et al. [92] conducted SA and UA of economic feasibility of establishing a ONWF in Kerman, Iran. OATSA of NPV with respect to inflation and currency rates was considered.

OATSA NPV of OFFWFs was found in [64][74][93][94][95][96][97]. OATSA of NPV was part of [64] (Section 2.2.3). NPV in [64] was found equally sensitive to icing and wind direction. A lifecycle techno-economic model of OFFWF for different entry and exit instances for a UK CS was created in [93]. The SAIVs were CAPEX parameters, OPEX parameters, revenue parameters, and financial expenditure parameters. OATSA revealed that financial and revenue parameters had a greater influence on the NPV of the investment in comparison to CAPEX and OPEX parameters [93]. The ranking of financial, OPEX and CAPEX parameters was established [93]. SA of NPV of a Spanish floating OFFWF (FOFFWF) was conducted in [74] using Oracle Crystall Ball [80]. The SAIVs included: wave parameters, W2 parameters, depth, distances, number of turbines, electric tariff, number of diameters between WTs, the diameter of WT, the diameter of the tower of WT, the height of the tower of the WT, WT cost, cost of direct labour in the shipyard, direct index labour in the shipyard, annual amortization in a mean shipyard, number of offshore wind floating platforms constructed by a shipyard in a year, percentage of financing, DR and cost of steel. W2 scale and the electric tariff was found most influential [74]. Shigina recently considered a design and a TEA of an OFFWF to be located in Murmansk region of Russia, as "". Shigina [96] recently considered a design and TEA of an OFFWF to be located in Murmansk Region of Russia, as "*adjacent Barents and White Seas are considered promising for wind energy utilization*" [96]. Her analysis included OATSA of NPV and IRR based on varying CAPEX and O&M costs. Ioannou et al. [97] published a preliminary techno-economic comparison of grid-connected and non grid-connected OFFWFs that included a OATSA of NPV presented in a spider diagram.

Although MC UA results can be easily translated into GSA results [13], OATSA of the NPV of an ONWF [76][86] and OFFWFs [94][95] was preferred to GSA. Pookpunt et al. [76] presented their comprehensive TEA for optimally placed WFs ambitiously calling it "*an ideal decision-making tool considering technical efficiency and profitability*" [76] that included both MC UA and OATSA of NPV. Haughton et al. [94] conducted an economic assessment of an OFFWF in Nantucket Sound, US, through MC UA and OATSA of NPV. The SAIVs were equipment and construction costs, WS, energy prices, the value of CO2 reduction, the value of SOx decline, the share of NG in electricity generation, O&M cost, the value of NOx reduction, the value of energy independence, and price of green credits. Equipment and construction costs and WS were reported to have the most impact on NPV. The SARs were presented in a *sensitivity chart*, widely known as TD. Ioannou et al. [95] looked into the stochastic financial appraisal of OFFWFs. They presented a probabilistic appraisal framework of OFFWF, used an ANN to model O&M costs and an ARIMA model to predict future electricity prices, and applied the MC approach to assessing system uncertainties. Although MC was used for UA, it was not used for SA. Instead, OATSA of NPV was implemented by increasing and decreasing twenty parameters by 20% from their baseline (expected values). The SARs were presented as a TD. The cost of the turbine component, the mean time to failure (MTTF), the foundation costs (FC's), the working hours and the weather adjustment factor were found to be most influential on the NPV [95]. The authors have a significant publication record on the topic of costs of an OFFWF, often use the MC approach [93][95][98][99], and consistently use SA in their analyses, but unfortunately always OATSA that do not provide reliable figures. An overview of different cost models for an OFFWF was found in [100].

2.3.2 Internal rate of return

IRR is calculated by solving (14) for *r*, entailing nonlinear relationships between all SAIVs and IRR, hence GSA should be used. Nevertheless, a single study [52] of the fourteen studies (8%) with IRR as SAOV used GSA instead of OATSA (92%). This statement serves as evidence of the prevalence of OATSA over GSA of IRR in WRA.

$$NPV = \sum_{i=0}^{N} \frac{B - C}{(1 + r)^{i}} = 0 \qquad => \qquad r = IRR \tag{13}$$

Richter et al. [52] conducted GSA of IRR alongside QMC UQ of three existing OFFWFs. The SAIVs included WS, wake effect, PC, SR, plant performance, capital cost, O&M cost, DR, and energy price. Wind contributes more than 80% of the uncertainty in IRR [52]. The other vital sensitivities include the PC, the O&M and capital costs. The wake effect has a negligible impact on IRR [52].

OATSA of IRR is commonly used [61][73][78][81][88][91][96][101][102][103][104][105][106] (See Section 2.3.1 for detailed accounts of [73][78][81][88][91][96][101]). Several FS's applied OATSA of IRR. Rafique et al. [102] conducted the thermo-economic feasibility of a Saudi ONWF for different climatic conditions (five locations) with RETScreen [68]. SA and risk analysis (RA) were included. The SARs were presented as a plot of IRR depending on the debt ratio. SA showed that zero-interest governmental loans were found to play an important role in the development of wind energy in Saudi Arabia [102]. Then results of RA were presented in the form of a plot resembling a TD. RA showed that the initial cost and O&M costs have the most impact on feasibility [102].

OATSA of IRR was also found in repowering studies [61][103] and GIS studies [104]. Villena-Ruiz et al.[61] found IRR to be most sensitive to the spot price. Colmenar-Santos et al. [103] looked into an actual possibility for WE in Spain in a new scenario without a feed-in tariff (FIT), i.e. repowering. IVs to SA of IRR were spot price, WT generator price, financial leverage, and profit taxes. The SARs were presented as plots of IRR vs. each input.

In GIS-related studies, SA seems to have a slightly different meaning from the mainstream. Grassi et al. [104] published GIS research with large-scale TEA of onshore WE potential for a CS in Iowa. The CS included a SA of the impact of the power purchase agreement on the land profitability [104]. All factors significantly affecting the cash flow of a wind project were accounted for (initial investment and O&M phase). Economic assumptions were made, but the core of the study referred to as SA were the five values of PPA, for which corresponding graphs of exploitable land area depending on IRR of wind project were plotted. From the mathematical modelling standpoint, such analysis, although useful and necessary in WRA, is not SA as SA aims to identify the IVs that make the most influence on the OV.

Again, a combination of MC UA and OATSA, this time of IRR, was found in [105], where financial additionality and viability of clean design mechanism projects under uncertainty was studied. Carmichael et al. [105] varied cash flows from their most likely values with and without carbon emission reduction. UNFCCC guidelines on the assessment of investing analysis were used, suggesting that SA covers *"a range of +10% and 10%"* [12]. Clearly, SA is unfortunately understood here solely as OATSA.

Zhang et al. [107] recently published a technical and institutional economics analysis of whether dispersed WP could take off in China. The study included SA of IRR and LCOE of dispersed WP under current institutional arrangement. Although the SA was used to "*ensure credibility of the results*" [107], OAT approach was used. SA inputs were initial investment, annual operational hours and financial arrangement, i.e. loan capital ratio and loan interest. Zhang et al. [107] report that SARs suggest that although all inputs have an effect on DWP, no matter the inputs there is considerate profitability in DWP. Based on this OATSA, policy implications were proposed [107].

Finally, Estanqueiro et al. [106] assessed maximum wind power penetration in weak grids using dynamic wind farm models. The inputs were the WS, lifetime, fuel, WT and O&M costs. The OATSAR was presented in a spider diagram with no established ranking.

A feasibility study by Sakka et al. [91] included an OATSA of IRR, for a detailed review refer to the previous Section.

2.3.3 Payback period

The payback period (PP) is the time necessary for capital investment to pay off. Roughly, a WT PP would amount to (15), where FIT is the wind electricity sell price. (15) is not a LM. Hence OATSA is not applicable, but the six studies reviewed in this section used OAT. Hence the absolute predominance of OATSA of PP is detected. OATSA of PP is also commonly used for hybrid systems with a wind component [108][109][110][111][112] that are outside the scope of this review. If the discounting of money in time is to be considered, it only adds to the nonlinearity of (15).

$$PP = \frac{CAPEX}{\mathrm{AEP} * \mathrm{FIT} - \mathrm{OPEX}}, \tag{14}$$

An early influential OAT study by Kaldellis et al. [113] on WT PP sensitivity equated the terms SA and OATSA: "[…] *it is important to define the central point of the proposed SA*". For example, Kongnam et al. [71] and a recent study of Tautz-Weinert et al. [64] are citing [113] and continue to apply OAT to SA of economic nonLMs. Kaldellis has an extensive publication record on SA of wind hybrid applications [110][111][112]. The SAIVs considered in [113] were capital cost, return on investment index, local inflation rate index, electricity price escalation rate, installation CF, M&O cost, turn-on key cost of the power plant, and rated power. Kaldellis et al. [113] found PP to be most sensitive to the capital cost, CF, and electricity escalation rate. A recent RETScreen [68] FS of a Saudi WF [102] (Section 2.3.2) included SA of PP with SAIVs such as electricity exported to the grid, electricity export rate, initial costs, O&M costs, debt ratio, and debt term. Waewsak et al. [84] (Section 2.3.1) conducted OATSA of PP with inputs such as project costs, AEP, and average tariff, but no ranking has been established as a result. Villena-Ruiz et al. [61] also conducted OATSA of PP in their repowering of a Spanish WF study (Section 2.3.1) with SAIVs such as spot price, WT generator price, financial leverage, and profit taxes. Villena-Ruiz et al. [61] found PP was most sensitive to SP, AEP, depreciation rate and O&M costs. Hadi et al. [78] performed OATSA of PP with RETScreen [68] for a single location in Iraq, initial cost was determined as most influential. Sgobba [114] recently defended her PhD thesis on on-site energy generation for a decarbonized Irish manufacturing industry, it included OATSA of wind application PP to DR, carbon tax, electricity and gas prices. Sensitivity of each input was considered individually and SA results were presented and plots of PP depending on DR, etc.

A common way to present OATSARs is in a TD. TD for PP of WFs can be found in SARs in [61][102].

2.3.4 Levelized cost of energy

LCOE is a popular SAOV in WRA, as this section is most populated. The interest in LCOE can be attributed to LCOE as a means to reason about grid parity [115] and the *breakeven price* of wind electricity [116]. Five [52][117][118][119][120] of the thirty nine studies (13%) reviewed used GSA, and 87% - OATSA, serving as evidence of the prevalence of OATSA of LCOE in WRA. Moving towards the use of the global MC approach to UA and SA of LCOE has been identified in [121][122][123]. Heck et al. [121] argued to use MC approach to integrate uncertainty into LCOE, instead of point estimates when assessing LCOE, especially that the technique is relatively simple. Lerch et al. [122] identified MC UA as a direction for future work. Aldersey-Williams et al. [123] brought forward a theoretical justification and critical assessment of LCOE and urged to use of the MC approach to model LCOE.

LCOE is a frequent SAOV in offshore WRA [52][74][95][116][117][120][122][124][125][126][127][128][129][130][131][132]. Borras Mora et al. [123] claim that "*a financial metric typically used in the energy sector to evaluate the financial performance of a project is the LCOE*" [133]. Recently Borras Mora et al. [120] applied GSA to offshore cost modelling. The study [120] included a GSA of LCOE based on the model, offshore cost modelling tool, developed and explained in detail in [123]. Also in [123] it was found that reducing the uncertainty in estimated mean WS does not necesserily improve the LCOE, and floating LIDAR technology is the optimal measurement campaign tool for offshore. Borras Mora et al. [120] point out that LCOE is a theoretical metric and as a result has a number of weaknesses, but it is commonly used in offshore wind. In [120] the variance (the Sobol) and density based (PAWN) GSA methods were compared with the results of SA of offshore LCOE. The total order ranking provided by the two methods coincided, the differences was in in secord order effects [120]. The key factors to drive the LCOE were found to be the WS (significantly higher than all others), target equity rate of return, WT costs, drilling costs, and debt service coverage ratio [120].

SA of LCOE of the forefront wind technology – FOFFWFs - was recently conducted [74][95][122][124][125][126], all used OATSA. [74][124] [125] used the same baseline of 100 5-MW WTs. Shafiee et al. [125] state this fact enabled them to compare their results to previous studies and validate the model. The same applies to the comparison of OATSARs of [74][124][125] that all use (15) to calculate LCOE. In (16) $CAPEX_i$ denotes investment in year *i*, $OPEX_i$ – maintenance in year *i*, AEP_i – energy generated in year *i*, and *r* denotes the DR. Here, the same observation as for the model of NPV can be made - the model is nonlinear. More ways to calculate LCOE can be found in [123] and [134]. SAIVs in [74][124][125] are given in *Table 2*.

$$LCOE = \frac{\sum_{i=1}^{N}(CAPEX_i+OPEX_i)/(1+r)^{\mathrm{i}}}{\sum_{i=1}^{N}AEP_i/(1+r)^{\mathrm{i}}}, \tag{15}$$

LCOE was found most sensitive to DR, distance from shore, farm size and depth in [124], W2 scale - in [74], and installed capacity of a WF, the distance from the beach, and the fault detection capability of a condition monitoring system – in [125].

Table 2: Sensitivity analysis input variables in [74][124][125]

	Castro-Santos et al. [74]	**Myhr et al.** [124]	**Shafiee et al.** [125]
SAIVs	wave height, wave period, W2 parameters, depth, farm-to-shore distance, distance from farm to the platform construction place,	farm size, distance to shore,	the capacity of OFFWF, site

	distance from farm to the component storage place, number of turbines, electric tariff, number of diameters between WTs, the diameter of WT, the diameter of the tower of WT, the height of the tower of the WT, WT cost, cost of direct labour in the shipyard, index direct labour in the shipyard, annual amortization in a mean shipyard, number of offshore wind floating platforms constructed by a shipyard in a year, percentage of financing, DR and cost of steel	water depth, project life span, eport cable, steel price, vessel rate, turbine, load factor, DR, contingency, and cost reduction	location, IR and the quality of fault detection

Lerch et al. [122] proposed a methodology for calculating LCOE for a specific FOFFWF and performed an extensive yet local SA with hundreds of SAIVs. Turbine, substructure and mooring system manufacturing cost, power cable cost was found to be the most influential variable besides the common DR and energy losses. Ioannou et al. [132] developed a parametric model for LCOE (16), CAPEX (19), and OPEX (20) based on WT rating, distance from shore, water depth, and WF capacity, the study included a OATSA of these outputs presented as plots of each output depending on each input. Ioannou et al. [95] performed a stochastic financial appraisal of OFFWF based on the deterministic lifecycle techno-economic model. They reported based on OATSA that the cost of the turbine, MTTF (hence, O&M cost), and FC to be most influential on the NPV and LCOE.They provide a thorough overview of costs related to OFFWF and assumptions for modelling them. Spyroudi [126] reported on the cost modelling analysis of floating wind technologies and assessed the potential of TLPWIND [135]. TLPWIND [135] is a 5MW Tension Leg Platforms floating technology for OFFWTs explicitly tailored for UK waters (Aberdeen coast). Spyroudi [126] conducted an OATSA of LCOE for TLPWIND [135]. SAIVs were exchange rate, turbine, fabrication, other OPEX, mooring and auxiliaries, O&M, export cable, installation, development, array cables, offshore substation, steel price, onshore substation, construction facilities, decommissioning, and landfall. LCOE was found in [126] to be most sensitive to the exchange rate and CAPEX.

$$LCOE = 110.37 P_{WT}^{-2.26} + 0.167WD + 0.004D^2 + 2.889\, 10^9\, P_{WF}^{-3.399} + 95.045, \qquad (16)$$

Where P_{WT} is WT rating, WD is water depth, D is distance from shore and P_{WF} is WF capacity.

SA of LCOE in conventional OFFWFs was found in [52][99][116][127][129][131]. A GSA (Sobol method) of LCOE of an OFFWF was found as part of the UQ in OFFWF [52] (Section 2.2.3). Levitt et al. [116] studied offshore WP pricing and conducted OATSA of breakeven price or LCOE when the NPV of costs is equal to the NPV of benefits:

$$\sum_{i=0}^{N} \frac{C_i}{(1+r)^i} = \sum_{i=0}^{N} \frac{AEP_i P_i + B_i}{(1+r)^i}, \qquad (17)$$

where C_i is the total cash expenditure including debt service payments, AEP_i is the annual energy production, B_i includes tax benefits and capacity payments, and P_i is the resulting LCOE (payback price equivalent to the possible energy price that year). The SAIVs were CAPEX, OPEX, CF, and DR. The OATSARs were presented as a linear plot of breakeven price vs. percentage of change. LCOE was found most sensitive to CAPEX, the DR, and CF in [116]. Yeter et al. [127] conducted a risk-based lifecycle assessment of offshore WT support structures accounting for economic constraints that contained an OATSA of LCOE. The SAIVs were DR, annual production, WTG price, FIT, steel price, OPEX, tax, and overhead. A TD demonstrated that the highest contribution to LCOE variation originated in the DR. Finally, Cavazzi et al. [129] used an offshore WE geographic information system (OWE-GIS) for the assessment of the UK's offshore WE potential. The study included OATSA of LCOE (calculated as (18)) based on changing values in IR, WF lifetime, availability, CAPEX, average WS, bad weather factor (double installation times were used to represent adverse weather conditions). SARs were presented as TDs [129]. The ranking of factors was established with IR and lifetime having the most significant influence on LCOE [129]. Jadali et al. [99] recently published their TEA of decommissioning (full and partial) vs. repowering of a hypothetical OFFWF in UK waters with a OATSA of LCOE. Inputs to SA were AEP, DR, installation and commissioning costs, O&M costs, production and acquisition costs, partial and full decommissioning costs, and repowering costs. The study included MC UA but OATSA of LCOE, SA found AEP to be most influential on LCOE. Xu et al. [131] recently reported on the status of offshore wind energy in China that included a OATSA of LCOE with respect to expected annual hours of utilization and unit cost and policy recommendations.

$$LCOE = \frac{1}{AEP} CAPEX * \frac{r}{1-(1+r)^{-n}} + OPEX, \tag{18}$$

Ebenbach et al. [136] compared the economics of conventional bottom-fixed and floating substructures used in OFFWFs with OATSA of LCOE for both. Inputs to SA of LCOE with bottom-fixed structures involved were the following: gross load factor, water depth, distance to shore, turbine size, and wind farm capacity. O&M, concrete price and weighted average of cost capital, were added to the list of inputs to SA of LCOE for FOFFWF design. The gross load factor was found most influential on both designs, while the influence of water depth is, understandably, more prominent on the conventional design.

Findings in this review concerning SA of LCOE in OFFWFs are in accordance with those outlined in "*Developments in Renewable Energy Offshore*" [137]. According to [137], economic factors like DR and lifetime have extensively been studies through SA [93][122][125][138], but "*sensitivity of the results to the years in which each of the costs occur has not been considered*" [137]. What is left to mention that although [93][122][125][138] made a significant input to the state-of-the-art of OFFWFs, all of them used OATSA.

Two studies with SA of both onshore and offshore borne LCOE are available in the literature [117][128]. Tran et al. [117] conducted a broad comparison study on LCOE of different energy sources (including onshore and offshore wind) that used the Sobol method [117]. Tran et al. [117] incorporated performance-based GSA and UA into LCOE calculations for emerging renewable energy technologies. SA for everyone (SAFE) toolbox [7] was used to conduct MC based GSA of LCOE for wave, tidal, pressure retarded osmosis, geothermal, biomass, hydropower, onshore wind, offshore wind, solar thermal, solar photovoltaic, nuclear, NG, and coal. The SAIVs were overnight capital cost, O&M cost, variable O&M cost, CF, lifetime, and lifecycle emissions. The GSARs were presented in a table with the mean, median and variance columns. Hence importance ranking was not established, despite having used GSA. The UA results labelled as GSA results signalled that UA and SA were used interchangeably. Schmidt et al. [128] assessed the costs of photovoltaic and WP (onshore and offshore) in six developing countries (Brazil, Egypt, Kenya, Nicaragua, India, Thailand). They conducted OATSA of LCOE and the incremental cost of wind electricity based on the changes in the target share of renewable energy technology (RET) in the electricity mix. Schmidt et al. [128] called the analysis SA, but only two values of a single input were calculated, and no further discussion of claimed SARs ensued. Such operation of the concept of SA in reputable journals such as Nature Climate Change points to the lack of standards concerning SA in the field of WRA. [5]

LCOE is often used in assessing onshore wind applications. Khalid et al. [62] conducted OATSA of generation cost for a 40 MW hypothetical Pakistani WF with RETScreen [23]. The SARs in [62] showed that the electricity production cost strongly depended on the initial project cost, electricity export price and electricity price escalation rate [62]. Tu et al. [115] studied the effects of DR, learning rate, curtailment rate, O&M cost, and CF for Chinese onshore wind electricity to reach grid parity in 2020. To this end, the OATSA of LCOE was conducted. Tu et al. [115] reported that high DR and O&M costs delay the moment of grid parity [115], with no ranking established. Ohunakin et al. [139] economically assessed WE conversion systems using LCOE and present value cost methods in Nigeria. OATSA of LCOE based on +/-10-80% changes in CF, civil cost, WT cost, project life, O&M cost, and IR was part of the analysis. The SARs were presented as a spider diagram. The SA revealed that the CF and the WT lifetime have a positive impact on LCOE, while the rest of SAIVs – a negative [139]. Gass et al. [140] assessed the economic WP potential in Austria. The changes in DR, lifetime, investment and O&M costs were considered [140]. The OATSA of LCOE [140] showed the existing FIT necessary to reach the set policy targets [140]. Also, DR had a significant impact on the resulting installed capacity [140]. Dong et al. [118] showed that QMC is superior to MC in WRA setting and found air density to be as important as Weibull scale parameter for a 1.5 MW WT operating in Zhangzhou onshore wind farm, both findings are similar to those of Tsvetkova et al. [13]. Recently, Dong et al. [119] published GSA results of a 1.5MW WT in commissioning Qingjing onshore wind farm in Eastern China, where Weibull scale parameter was found most influential. Both SA studies [118][119] used air density, Weibull shape and scale parameters as inputs, LCOE as output, and Sobol SI as SA method. Sgobba [141] published on sensitivity of on-site renewable electricity production and self consumption for manufacturing industry in Ireland to techno-economic conditions, the article included a OATSA of wind LCOE to normalized CAPEX and DR.SA of LCOE based on changes in HH was part of [140] (Section 2.2.3). Since the input was only one, it automatically classifies this instance of SA as OAT. Adaramola et al. [142] assessed WP generation along the coast of Ghana with OATSA of LCOE for the location of Oshiyie. SAIVs were project lifetime, DR, CF, cost WT, and civil cost contribution. Adaramola et al. [142] classified SAIVs into two groups: CF and the useful lifetime of the WT had a positive effect on LCOE, while the rest – harmful. Herran et al. [143] performed a global assessment of coastal WP resources, considering the distance to urban areas. OATSA of LCOE was part of the study. Aggregated distance to an urban area, transmission losses, transmission cost, visibility, land use factors (land suitability factor, the density of capacity), technical factors (array efficiency, availability), and economic factors (capital cost, DR, lifetime) were considered for the SA. The SARs were presented in a TD. SAR suggests that the distance to urban areas is insignificant for the global availability of onshore wind resources [143]. Sunderland et al. [144] compared urban WTs and solar PV systems in Ireland with OATSA of LCOE produced by HOMER [145]. The IVs to SA referred to as "*design of experiment analysis*" [144], were the following: capital, resource and IR, but no ranking of inputs was established. The SARs revealed dependency rather than ranking, i.e. the WT productivity was

[5] This problem is not unique to WRA.

concluded to be dependent on wind speed [144]. Ali et al. [79] (Section 2.3.1) conducted OATSA of LCOE for three locations in South Korea.

Tizgui et al. [100] estimated wind LCOE in Morocco. The SAIV were IR, O&M costs, AEP, lifetime, which all were found to have a significant influence on LCOE, except for O&M costs according to plots of LCOE depending on each input. Allouhi et al. [101] conducted an energetic, exergetic, economic and environmental (4E) assessment of onshore WP generation in Morocco with OATSA of LCOE. The SAIVs were air temperature, DR, and CF. Allouhi et al. [101] found LCOE to be most sensitive to the CF, and DR. Galvez et al. [102] researched how the change in DR, O&M costs and investment costs affect LCOE (SA) for a CS in Mexico. The SA [102] revealed the need to implement financial mechanisms like a FIT to decrease the electricity production cost in low-potential areas. Barutha et al. [130] evaluated the commercial feasibility of a new tall wind tower design concept using a stochastic LCOE model.

Carriveau et al. [146], Rubert et al. [147][148], and Jadali et al. [99] recently contributed to the important and necessary debate on extending options for ONWFs, all reasoned based on unreliable OATSA of LCOE. Carriveau et al. [146] looked at the situation in Canada as "*the wind fleet in North America is aging, with farms approaching and surpassing the halfway points of their power purchase agreements*" [146], while Rubert et al. [147][148] and Jadali et al. [99] – in the UK.

2.3.5 Capital expence

Mytilinou et al. [149] recently conducted a techno-economic optimisation of OFFWFs based on life cycle cost analysis in the UK, where GSA of CAPEX and OPEX with respect to layout, number of WTs, WT size and site name was part of the study. GSA included calculation of total, first and second order Sobol indices. Second order Sobol indices correspond to pairwise sensitivity, or more precisely determine the amount of output variance that is explained by the respective pairwise interaction. It also included OATSA of CAPEX and OPEX for the optimal layout solution determined. SA was carried out with SALib [150]. The SA completed depicted "*the highly complex nature of the decision variables and their interdependencies, where the combinations of site-layout and site-turbine size captured above 20% of the variability in CAPEX and OPEX*" [149].

Martinez-Luengo [151] developed guidelines and showed a CBA of the structural health monitoring implementation in offshore wind with a CS on the UK. The study included a OATSA of CAPEX and OPEX. OPEX reduction due to structural health monitoring implementation was observed.

Two studies by a prominent group of researchers in offshore wind, Ioannou et al. [132] [152], applied OATSA to CAPEX. In [132] they developed a parametric model for CAPEX (19) based on WT rating, distance from shore, water depth, and WF capacity, a OATSA of CAPEX was presented as plots depending on each input. In [152] they presented a preliminary parametric techno-economic study of offshore wind floater concepts. (19) shows the underlying nonlinear relationships. Borras Mora [120] too argued in favor of GSA for cost models in offshore wind due to the complex nature of the relationships between the inputs and outputs of such models.

$$CAPEX = -1.485\ 10^{11} P_{WT}^{0.001} + 2.353\ 10^{6}\ WD + 2.53\ 10^{6} D + 2.451\ 10^{6}\ P_{WF} + 1.487\ 10^{11} \quad (19)$$

Where P_{WT} is WT rating, *WD* is water depth, *D* is distance from shore and P_{WF} is WF capacity.

2.3.6 Operational expense

Martin et al. [153] thoroughly considered the project three stages of OFFWFs in terms of O&M costs, as they account for 14-40% of project life expenditure. Qualitative screening SA (the Morris method [1]) was applied, and the results showed that "*access and repair costs along with failure rates for both minor and major repairs*" are the factors contributing the most to total O&M costs [153]. The use of the Morris method is rightfully justified as the OFFWF O&M model used in [153] had over a hundred inputs, and the model execution time was measured in minutes. SA framework, recently announced to no longer be available for downloading, SimLab [154] was used for the described SA experiment. *Sensobol* R package [11] can be now used instead.

Aforementioned Ioannou et al. [132] developed a parametric model for OPEX (20), a OATSA of CAPEX was accompanying. (20) shows the underlying nonlinear relationships.

$$OPEX = -6.349\ 10^{8} P_{WT}^{0.187} + 2.595\ 10^{-19} e^{0.83D} + 8.414\ 10^{5}\ P_{WF} + 9.506\ 10^{8} \quad (20)$$

Where P_{WT} is WT rating, *WD* is water depth, *D* is distance from shore and P_{WF} is WF capacity.

Some articled reviewed in previous section included SA of OPEX in them. For a detailed review of Mytilinou et al. [149] and Martinez-Luengo [151], refer to the previous Section, and of Dykes [53] – to Section 2.2.2.

3 Sensitivity analysis methods

This section briefly explains the SA methods that were encountered during the review to be used in WRA. Section 3 classifies the review pool articles based on the class of SA method used: 3.1 Local sensitivity analysis including subsection 3.1

Local SA (LSA) uses derivative-based measures of sensitivity $\partial Y/\partial X_i$ that characterize an individual effect of each input at a specific point in space (base point), hence the name local. Such measures are only valid locally, in close vicinity to the base point. The exception is the linear model when the first partial derivative is constant.

One-at-a-time sensitivity analysis oi not a method of SA per se, rather it is an example of convenience sampling from the design of experiment (DOE) point of view. Nevertheless, the review reveals that OATSA is especially popular in WRA.

The choice of the proper SA method depends on the following considerations:

- The computational cost (number of model runs) of calculating the model for a given point in space (a combination of inputs)

- The number of inputs
- Linearity/nonlinearity of the model
- The consideration of interactions among the inputs in the model (typical for nonLMs)

3.1 Local sensitivity analysis

Local SA (LSA) uses derivative-based measures of sensitivity $\partial Y / \partial X_i$ that characterize an individual effect of each input at a specific point in space (base point), hence the name *local*. Such measures are only valid locally, in close vicinity to the base point. The exception is the linear model when the first partial derivative is constant.

3.1.1 One-at-a-time sensitivity analysis

Misinterpretation of SA as the practice of changing one parameter at a time, and tracking the effect such change has on the OV is frequent. In such studies, a baseline case is chosen. Then an increase or decrease of a certain amount usually measured in percent is applied to one parameter, and the result it has on the variable of interest is analyzed. Hence the name - one-at-a-time (OAT) or one-factor-at-a-time. OATSA was called "*one-factor*" in [59] and "*what-if*" analysis in [64]. OATSARs are often presented in TDs (Figure 5). OAT is one of the most common and most straightforward approaches to SA. Despite its simplicity, it does not explore input space adequately - the higher the number of inputs, the weaker the exploration of space [13]. OATSA is invalid for nonlinear models [21]. Moreover, OAT does not account for interactions among the inputs [4]. OATSA approximates LSA. Therefore, the validity of OATSARs holds only for linear models. OATSA is commonly used for SA in WRA [13]. OAT was applied for SA of GOFMs, WP, WE, NPV, IRR, PP, LCOE. CAPEX and OPEX in WRA (*Table 3*).

Table 3: One-at-a-time sensitivity analysis review pool articles organized by sensitivity analysis output variable

SAOV	Reference
GOFMs	[33][34]
WP	[35][43]-[48]
WE	[52][58]-[65]
NPV	[52][60]-[62][70]-[122][81]-[95]
IRR	[52][61][73][81][88][101]-[106]
PP	[61][113][84][102]
LCOE	[124][52][74][122][95][116][125]-[129]
CAPEX	[132][151][152]
OPEX	[53][132][151][153]

3.2 Global sensitivity analysis

The present section briefly covers some of the GSA methods that are applied in the field of WRA. Saltelli et al. [155][8] claim that GSA is the common notion that modern-era SA has focused on in the last twenty years. A recent overview of state-of-the-art of SA distinguished four major GSA approaches: (1) derivative-based, (2) distribution-based, (3) variogram-based, and (4) regression-based [8].

3.2.1 Scatterplot method

If inputs X_i are sampled and the model's response $Y(X_i)$ is recorded. Hence output *Y* is sampled too. Plotting $Y(X_i)$ provides information about the model's behaviour. The higher the correlation between $Y(X_i)$ the most influential X_i is on *Y*. Saltelli et al. [4] claim that little shape of the cloud of points over the range of the input factor (like *X1* or *X5* in Figure 7) is a definite sign that the input is less influential. Saltelli et al. [4] point out that the scatterplot method is a straightforward and informative way to conduct SA and that "*most SA measures derived by practitioners aim to preserve the rich information provided by the scatterplots in a condensed format*" [4]. Function *plot_scatter* of *sensobol* R package [11] is one implementation of the method. Saltelli et al. recommend taking a sample of size N = 1000. Scatterplots were found in SA in WRA in [53].

3.2.2 The Morris method

The Morris method [1] for screening, or eliminating non-influential factors, also known as the elementary effects method, is usually used for reducing models dimensionality so that computation of variance-based methods would become feasible. In 1991 Morris [1] introduced a screening method that is in essence a OAT sampling design dividing the *k*-dimensional input hypercube space (for a model $Y = f(X) = f(X_1, X_2, \dots, X_k)$ of *k* variables) into *p* level grid. Sampling along *l* (typically *l* ~ 4-10) trajectories consisting of *k+1* points produces two sensitivity measures mean μ (19) assessing the overall importance of the input and σ (20) – the interactions and nonlinear effects. Campolongo et al. [2] offered an improved measure μ* (22). The elementary effect $d_i(X)$ for each input is defined as (19), where *Δ={0, 1/(p-1), 2/(p-1), … 1}*. The method is implemented as *morris* function in *sensitivity* R package [156]. The Morris method was used for SA of OPEX in a single study by Martin et al. [153].

$$d_i(X) = \frac{f(X_1, \dots, X_i + \Delta, \dots, X_k) - f(X)}{\Delta} \tag{21}$$

$$\mu_i = \frac{1}{l}\sum_{j=1}^{l} d_i\left(X^{(j)}\right) \tag{22}$$

$$\sigma_i = \sqrt{\frac{1}{l-1}\sum_{j=1}^{l}\left(d_i\left(X^{(j)}\right) - \mu_i\right)^2} \tag{23}$$

$$\mu_i^* = \frac{1}{l}\sum_{j=1}^{l} \left|d_i\left(X^{(j)}\right)\right| \tag{24}$$

3.2.3 The Sobol method

The Sobol method is a well established variance-based method of GSA, also referred to as "*the golden standard of SA*"[157]. It includes the calculation or estimation of first-order and total-effect sensitivity indices (SIs) as measures for establishing a ranking among the inputs. In 1990 Sobol [3] published the proof of the theorem about the decomposition of an integrable function into summands of different dimensions in a Russian journal and defined the Sobol SIs. The SIs are the measures of variance that brings about the ranking of variables. In the case of independent inputs, the first-order SIs are sufficient for establishing a ranking of inputs. If the dependency of some IVs is present, or the model is nonlinear, the calculation of total-effect indices is necessary as well. Total-effect SI's account for dependencies and higher-order effects (or interactions) among the inputs. Later the Sobol SIs made their way into the English speaking scientific community [158][159] and well established itself in a variety of disciplines [22][160][161] due to its universal applicability with the assumption of input independence.

The crux of the Sobol method lies in using analysis of variance (ANOVA) decomposition as a sensitivity measure. If the model $Y = f(X) = f(X_1, X_2, \dots, X_k)$ is a function of k variables, () defines the first-order SI's $S_i(Y)$and (24) – the total-effect SI's $T_i(Y)$ for the function Y [159]. A multitude of estimators of these indices (four estimators of first order and five - of total order SI's) can be calculated by calling *sobol_indices* function in *sensobol* R package [11].

$$S_i(Y) = \frac{V_i}{V(Y)} = \frac{V_{X_i}(E_{X\sim i}(Y|X_i))}{V(Y)} \tag{25}$$

$$T_i(Y) = \frac{V_{T_i}}{V(Y)} = \frac{E_{X\sim i}(V_{X_i}(Y|X_i))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}\left(E_{Xi}(Y|X_{\sim i})\right)}{V(Y)}, \tag{26}$$

Where *V(Y)* is the model variance, $V_{X_i}(E_{X\sim i}(Y|X_i))$ is the variance based on the first-order effect for the input variable X_i. $X_{\sim i}$ excludes the effect of the variable X_i.

There is a number of estimators of the total order effect indices defined in (30). In a recent "*battle of total-order sensitivity estimators*" [157] by Puy et al., the estimator by Razavi & Gupta [162] took over the rest and should be preferred in practice. An implementation of this estimation procedure by Razavi & Gupta [162] is available in *sensobol* R package [11]. Sobol's method was used in SA of WP [35][38][42], WE [13][52][53][67], NPV [52], IRR [52] and LCOE [52][117][120], OPEX [149].

3.2.4 Extended Fourier amplitude sensitivity test

Another way to calculate SI's is through variance decomposition based on multiple Fourier series. The Fourier amplitude sensitivity test (FAST) translates a multivariate SAOV into a single frequency variable with the use of the Fourier series. Therefore, the integrals required to calculate the SI's become univariate, resulting in significant computational savings. Cukier et al. [163] first suggested the use of FAST for GSA in his research on nonlinear SA, and Saltelli et al. [164] introduced an alternative way to compute FAST for GSA purposes, i.e. the extended FAST (eFAST). eFAST is implemented as *fast99* function in *sensitivity* R package [165][156]. The effects of WMs on WP with eFAST were studied in [36][37].

3.2.5 Shapley effects

Owen [166] introduced the concept of the Shapley value [167] from cooperative game theory into GSA. Shapley value [167] is a "*fair*" distribution of the total gains to the players of the game, assuming they all collaborate. Owen [166] found the Shapley value of individual variables when "*variance explained*" was taken as their combined value, and showed that Sobol first-order and total SIs as being easier to compute serve as the bound for the new sensitivity measure, which adds up to total variance in case of independent inputs. Soon after Song et al. [54] called this measure in case of dependent inputs Shapley effects and showed how Sobol first-order and total effect SIs, "*even when used together, may fail to appropriately measure how sensitive the output is to uncertainty in the inputs when there is probabilistic dependence or structural interaction among the inputs*" [54]. They also proposed an efficient MC algorithm for estimation of Shapley effects (function *shapleyPermRand* in *sensitivity* R package [156]). Another estimation procedure for Shapley effects was recently proposed by Goda [168]. The use of Shapley effects in SA in WRA was found in a single review pool article – SA of WP by Carta et al. [39].

3.2.6 PAWN

A novel and efficient GSA method called PAWN was introduced by Pianosi et al. [6] in 2015. The essence of PAWN is an efficient computation of density-based SI's. The efficiency lies in characterization of output distributions by their Cumulative Distribution Functions (CDF) instead of PDFs, as CDFs are easier to derive than PDFs [6]. Pianosi et al. [6] demonstrate the advantages of PAWN through a series of applications to numerical and environmental models. PAWN was designed to be a complementary approach to variance-based GSA [6]. Later in 2018 a generic estimation procedure was proposed by the same group to make the application of PAWN easier for the practitioner [169]. The method can be easily accessed through SAFE toolbox [7]. Borras Mora [120] was the only study in the review pool to apply PAWN for SA of offshore LCOE.

4 Offshore vs. onshore

This section classifies the reviewed article pool into offshore and onshore wind applications (*Table 4*). Not a single GSA of GOFM or PP was found in the literature. No SA of PP of offshore applications was detected.

According to the review, offshore wind development is of special significance to the UK and Spain. The costs of offshore wind has been dropping in the last years, making the more abundant offshore wind potential feasible for integrating into the grid. According to Borras Mora [120], "*simple cost models are no longer suitable*" [120] for assessing profitability of the next generation OFFWFs, "*tailored techno-economic cost models are being developed*" [120], those that capture the new relationships formed due to rapid technological advancement and policy incentives. GSA is necessary to study these models are complex and the relationships between inputs and outputs are poorly understood [120].

As a side note, novel methods of GSA are used in structural analysis and safety studies in offshore applications. Teixeira et al. [170] used transformed Kullback-Leibler divergence for GSA of short-term stress damage rate of an offshore WT. Velarde et al. [171] performed variance-based GSA of offshore wind foundation loads using MC. Such studies are outside the scope of this review but are worth mentioning due to the application of GSA to offshore wind. Zhou et al. [172] conducted GSA on the semisubmersible substructure of a WT of a FOFFWF.

Table 4: Review pool articles organized by objective and application

	GOFM	WP	WE	NPV	IRR	PP	LCOE	CAPEX	OPEX
Offshore	-	[37] [42]	[52]	[52][72] [74][77]	[52]	-	[52][74] [95] [99]	[132] [151]	[132] [149]

		[43]		[94][95] [97]			[116]-[129][131] [132]	[153]	[151] [153]
Onshore	[33] [34]	[35][36] [38][39] [45]-[48]	[13] [53]- [67]	[60][61] [70][71][73] [75]-[78] [80][81][83] -[86][87] [91][92] [96][122]	[61] [73][78] [81][88][91] [96][101]- [106] [107]	[61] [78] [84] [102] [113] [114]	[62][79] [107] [115][117]- [119] [128][129] [139]-[173]		[53]

5 Geography

Section 5 intends to uncover research gaps in the literature. Since there is plenty of wind data available online, when designing a WRA CS for scientific purposes, this section serves as a quick reference on understudied regions of the world. In the process of the review case studies with meteorological data from thirty-seven countries (Figure 1) with SA in one form or another were encountered, Table 5 classifies these findings based on the country and SA model. Global and selected country reports concerning installed wind capacity can be found in [174] with detailed information on operating WFs across the world.

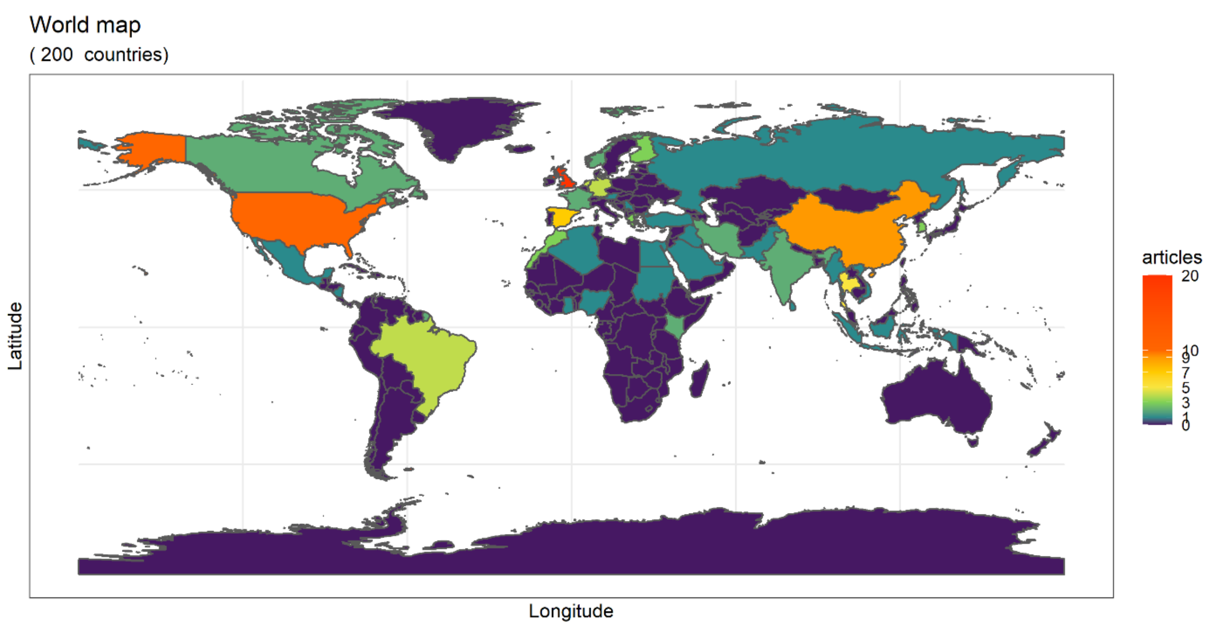


Figure 1: Geographical representation of the review pool

The main review findings from the geography standpoint are that (1) LCOE is the most popular SAOV, and (2) the UK, the US and China are the most studied countries in terms of the number of SA studies in the literature.

Table 5: Review pool articles organized by country and model

	GOFM	WP	WE	NPV	IRR	PP	LCOE	CAPEX	OPEX
Algeria		[48]							

Austria							[140]		
Brazil				[85][86][87]			[128]		
Canada		[36]					[146]		
China		[45]			[107]		[81][107] [118] [119] [131] [175][176]		
Egypt							[128]		
France			[67]				[122]		
Finland			[60]	[60][77]					
Germany	[34]			[52][77]	[52]				
Ghana							[142]		
Greece				[91]	[91]	[113]			
India							[128][177]		
Indonesia				[81]	[81]				
Iran	[33]			[92]					
Iraq				[78]	[78]	[78]			
Kenya				[70]			[128]		
Mexico							[173]		
Morocco		[42]					[178][179]		
Myanmar				[73]	[73]				
Netherlands			[52] [64]	[64][77][95]	[52]		[52][95]		
Nigeria							[139]		
Nicaragua							[128]		
Norway		[38]					[124]		
Pakistan			[62]				[62]		
Russia				[96]	[96]				
Saudi Arabia					[102]	[102]			
Serbia				[75]					
South Korea				[79][88][180]	[88]		[79]		
Spain		[39]	[61] [63] [64]	[61][64][74]	[61][74] [103][106]	[61]	[74][63]		
Sri Lanka							[181]		
Sudan				[182]					
Turkey				[101]	[101]				
Thailand				[71][76][83][84]	[84]	[84]	[128]		
UAE			[13]						
UK		[35]	[64]	[64][72] [93][97] [183]		[114]	[99][120] [122][123] [126][129] [132] [141][144] [147][148]	[132] [149] [151]	[132] [149] [151] [153]
US		[43]	[53]	[53][65][94] [184]	[104]		[116][117] [122][130]		[53]
Vietnam		[46]							

6 Software

Section 6 classifies the article pool based on the software used for SA and discusses the influence each tool has on the choice of the SA method. Douglas-Smith et al. [22] identified the software for UA and SA and provided an overview of the general research trends. Murphy et al. [185] published a review of software tools used in WRA[6]. The software used for SA in WRA is listed in *Table 6*. Often wind-related projects are analyzed with the use of professional modelling software targeted for modelling clean energy projects, for example, RETScreen [68][110]. RETScreen[7] is used for a feasibility assessment of clean energy projects [62][68][73][78][102], the only available option for SA of NPV in RETScreen is OAT. The nonlinear nature of models in WRA and economics is disregarded.

Pianosi et al. [7] created a Matlab toolbox called "*Sensitivity analysis for everyone*" (SAFE) aiming to popularize GSA[8]. Tsvetkova et al. [13] used R for GSA. *Sensitivity* package in R [156] provides easy-to-use access to screening and GSA methods. Noacco et al. [186] provided a handy set of workflow scripts (R/Matlab) and discussed the critical choices that potential GSA users would face [186].

Oracle Crystall Ball [80] User Guide [187] gives information both on TDs implying OATSA [188] and correlation coefficients implying GSA [189]. Commercial software [80][82][135] commonly use OATSA regardless of the model at hand. Open source toolboxes specializing in SA [7][165] are using GSA methods. For instance, a framework for unified systems engineering and design of wind plants (FUSED-Wind), an open-source framework intended or multi-disciplinary optimization and analysis of wind energy systems, that defines key interfaces, methods and inputs and outputs "*to achieve a system level analysis capability of wind turbine plants with multiple levels of fidelity*" [5]**,** implements the Sobol method.

Table 6: Review pool articles organized by software and sensitivity analysis method

Software tool/SA method	**OAT**	**Morris**	**Sobol**	**Scatterplot**
Excelbased @RISK [82]	[81]			
Excelbased Oracle Crystal Ball [80]	[74][75][122]			
Matlab based GUI-HDMR [51]			[35]	
Matlab/R/python based SAFE [7]			[117]	
Matlab-based UQLab [57]			[40]	
Pythonbased WISDEM [69]			[53]	[53]
Pythion based SALib [150]	[149]		[149]	
Python based FUSED-Wind [5]			[53]	
R [165]			[13]	
Standalone RETScreen [68]	[62][73][78][102]			
Standalone SimLab [154]		[153]		

Although the application of GSA is yet in its infancy, the availability of software tools and packages for GSA is surprisingly vast [11] for any taste and budget. So, unavailability of tools is not the reason for slow uptaking of GSA. The authors used the *sensobol* R package [190] for the

[6] The list included RETScreen, RETScreen Plus, FOCUS, FAST, QBlade, Vortexje, WAsP, OpenWind, WindPRO, Windsim, and Metodyn [185].

[7] Developed by Natural Resources of Canada.

[8] The authors report how well the open-source project has been adopted in [112].

examples in Section 8 and found it very easy to use (R script can be found in supplementary materials).

Table 7: Overview of software tools for global sensitivity analysis [8][11]

Software tool/Language of implementation	**R**	**Matlab/Octave**	**Python**	**C**	**C#**	**C++**	**julia**
SALib [150]			x				
SAFE [7]	x	x	x				
UQLab [191]		x					
sensobol [11]	x						
sensitivity [190]	x						
fast [192]	x						
multisensi [193]	x						
SobolGSA [194]		x	x		x		
Dakota [195]						x	
OpenTURNs [196]			x			x	
PSUADE [197]				x			
VARS-Tool [198]		x		x			
MADS.jl [199]							x
FUSED-wind [5]			x				

For scientists more familiar with SA looking to compare, for instance, different estimators of Sobol indices for a given model, can do so with the new *sensobol* package, that offers four estimators (classic Sobol [200] and Jansen [201] estimators, plus more recent [202]). According to the benchmark of Puy et al. *sensobol* [11] is twice as fast as *sensitivity* R package [190].

Table 8: Comparison of sensitivity analysis tools and methods implemented

Software tool/SA method	**Shapley effects** [54]	**Morris method** [1]	**Borgonovo indices** [191]	**Sobol indices** [159]	**Kucherenko indices** [57]	**FAST**	**PAWN** [6]
SALib [150]		x		x		x	
SAFE [7]		x		x			x
UQLab [191]		x	x	x	x		
sensobol [11]				x			
sensitivity [165]	x	x		x		x	
fast [192]						x	
Multisensi [193]				x		x	

7 Specifics of application

To illustrate the misleading or erroneous inference that OATSA can entail for some models, consider three examples in this section. *Sensobol* R package [11] with a sample size of a 1000 was used for the three examples, the R script is provided in supplementary materials.

7.1 Example I: Linear model

Consider a linear model $L = X1 + X2 + X3 + X4 + X5$ with all inputs uniformly distributed in [0,1]. For such a simple model obviously OATSA and complex GSA methods would produce identical results (Figures 2-5). It's worth mentioning that Sobol indices provides more information about the model at hand. For a linear model, no interactions of factors are present, similar values of first order and total effect indices in Figure 4 confirm this.

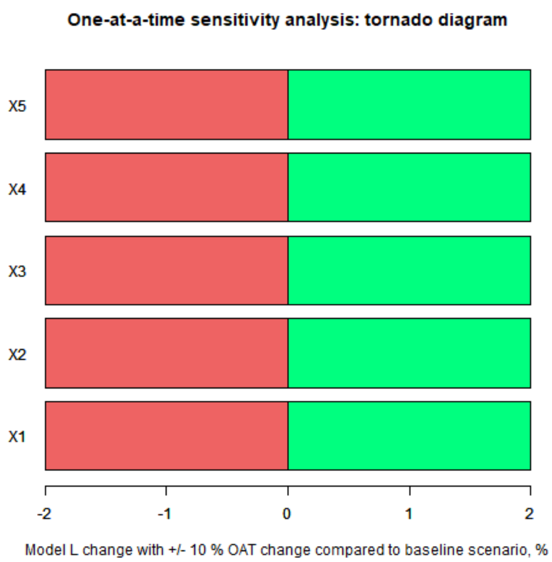


Figure 2 : One-at-a-time sensitivity analysis results for model L and uniformly distributed inputs

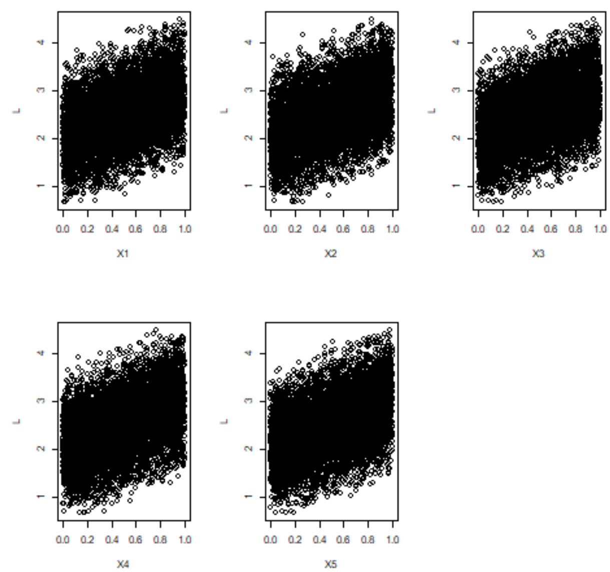


Figure 3 : Scatter plot for model L and uniformly distributed inputs

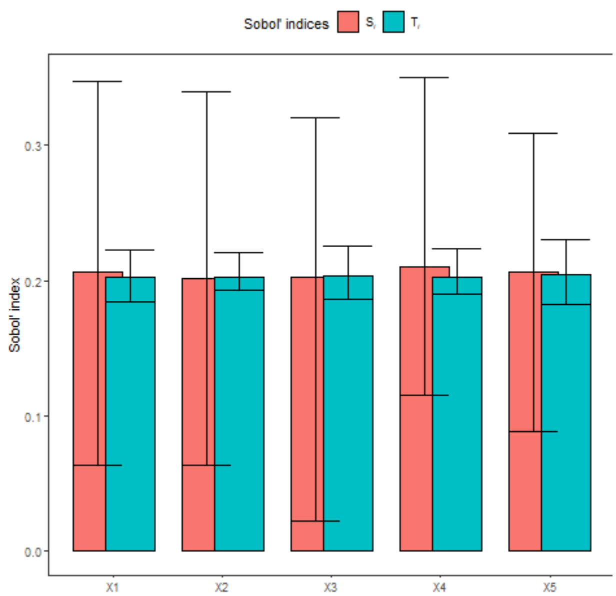


Figure 4 : Sobol indices for model L and uniformly distributed inputs

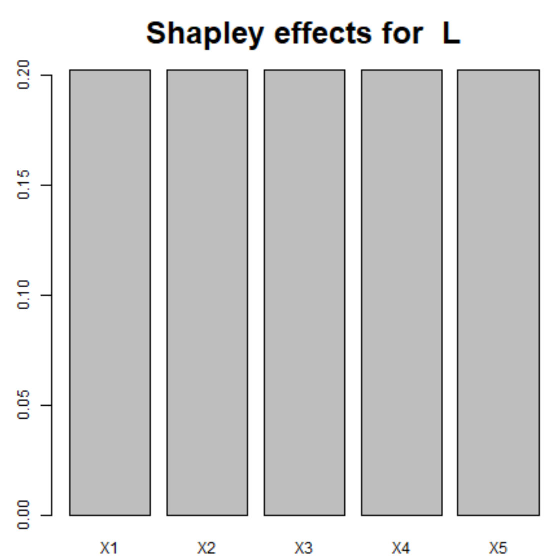


Figure 5 : Shapley effects for model L and uniformly distributed inputs

If the variables would now be distributed normally in the following manner *X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01),* SA results would be quite different and this subtle change in distributions would only be detected by the savvy GSA methods (Figures 7-9). According to OATSA *X4* is most influential on *L,* while the GSA methods - scatterplot, Sobol and Shapley – all agree that it is *X3*. This example illustrates that OATSA can even be misleading for a LM, because SA results depend on the model, the distributions of the inputs, and interactions among the factors.

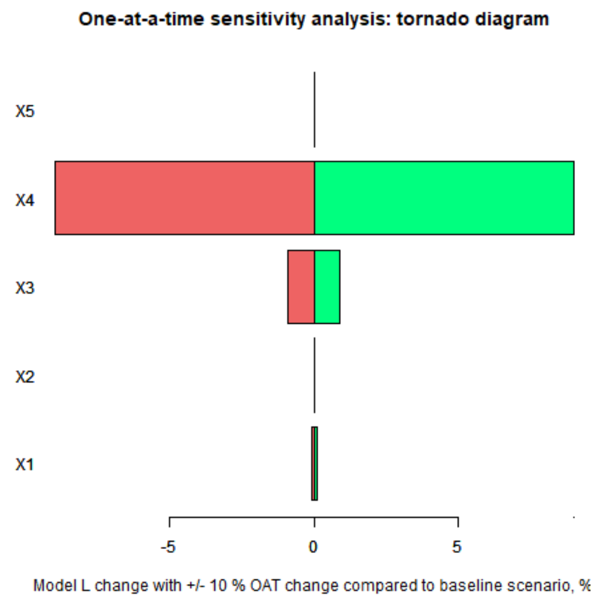


Figure 6 : One-at-a-time sensitivity analysis results for model L and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

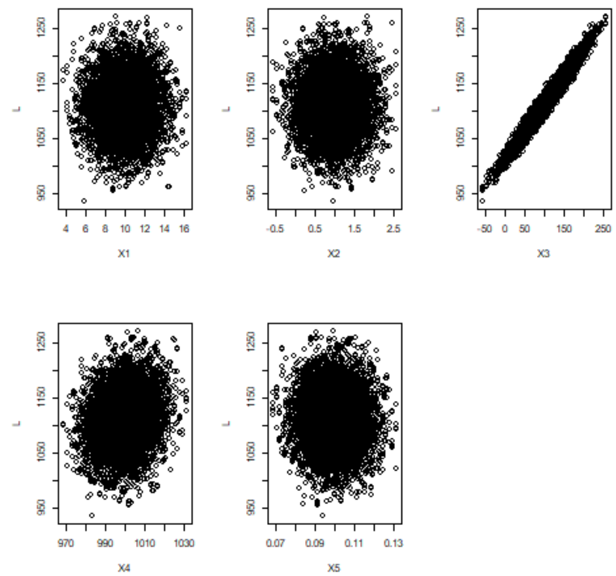
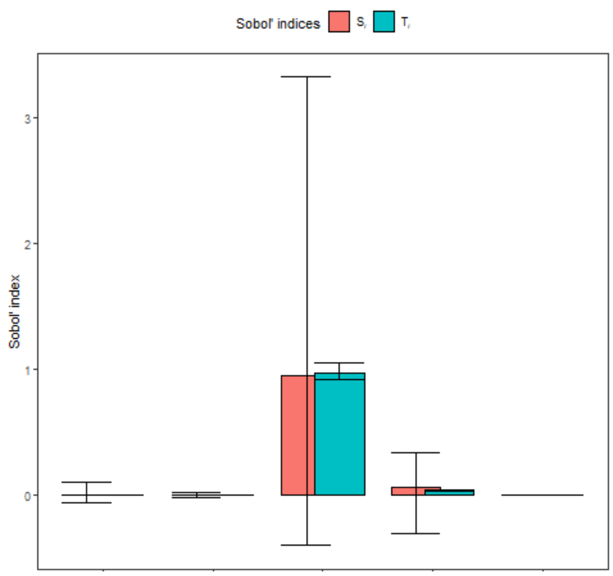


Figure 7 : Scatter plot of model L and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)



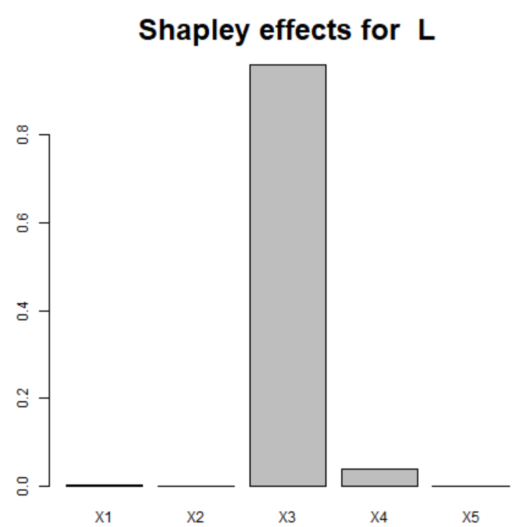


Figure 8: Sobol indices for model L and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

Figure 9: Shapley effects of model L and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

7.2 Example II: Nonlinear multiplicative model

Now consider a multiplicative model *M = X1*X2*X3*X4*X*5 with all inputs uniformly distributed in [0,1]. Although, OATSA and GSA results coincide in this particular instance, it can be seen in Figure 12 that for model *M*, all factors interact with one another (values of total effect SI's are much greater than first order SI's). This is an example of the Sobol method providing fuller information about the model compared to the OATSA, even when the ranking provided by both are the same.

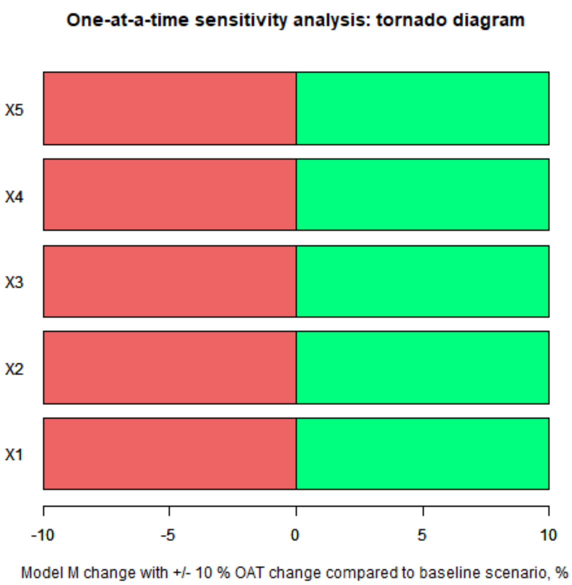


Figure 10 : One-at-a-time sensitivity analysis results for model M and uniformly distributed inputs

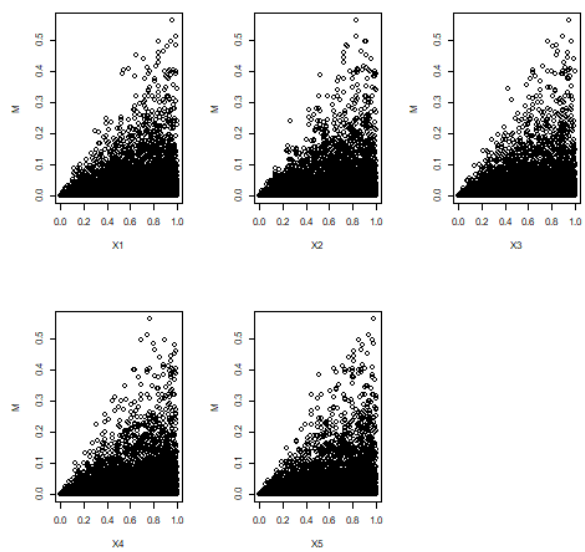


Figure 11 : Scatterplots for model M and uniformly distributed inputs

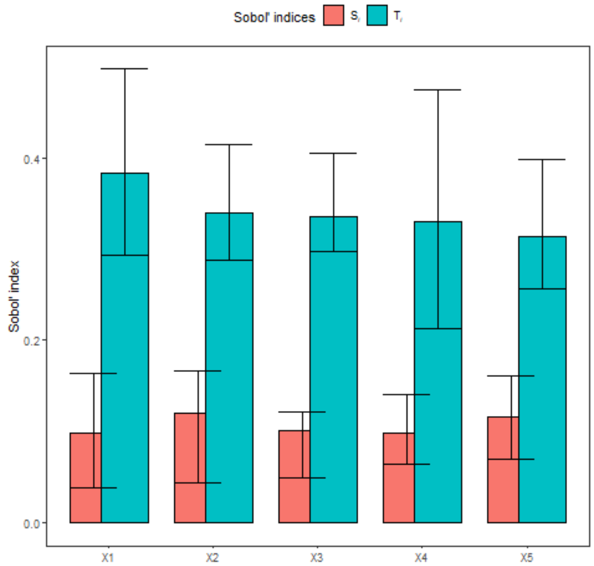


Figure 12 : Sobol indices for model M and uniformly distributed inputs

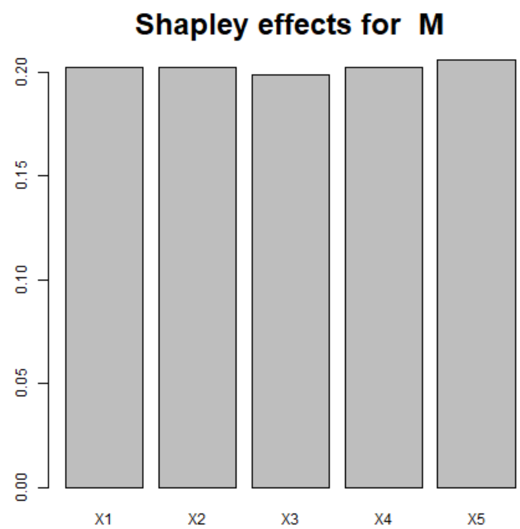


Figure 13 : Shapley effects for model M and uniformly distributed inputs

Now again the variables are distributed normally in the following manner *X1 ~ N(10,2), X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)*. This change again remains unnoticed to the OATSA (Figure 14), but is picked up by the GSA methods, that again agree in their findings on the most influential factors being *X2* and *X3* (Figures 15-17).

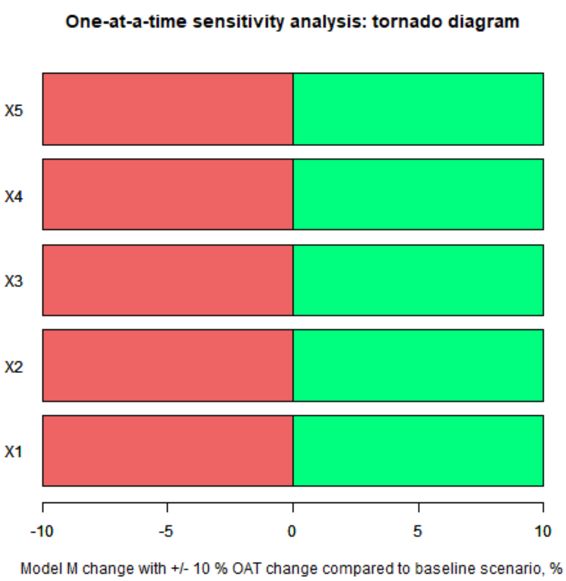


Figure 14 : One-at-a-time sensitivity analysis results for model M and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

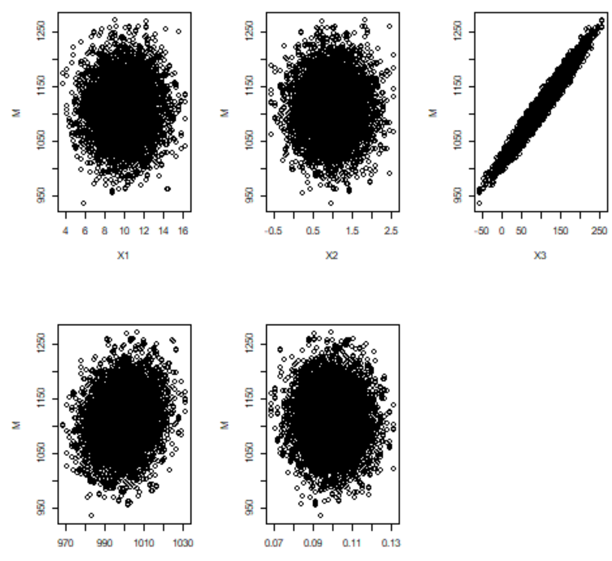


Figure 15 : Scatter plot of model M and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

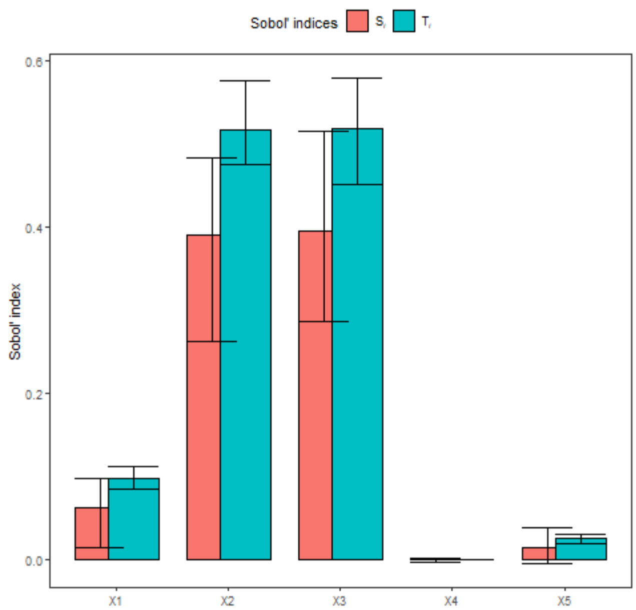


Figure 16: Sobol indices for model M and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

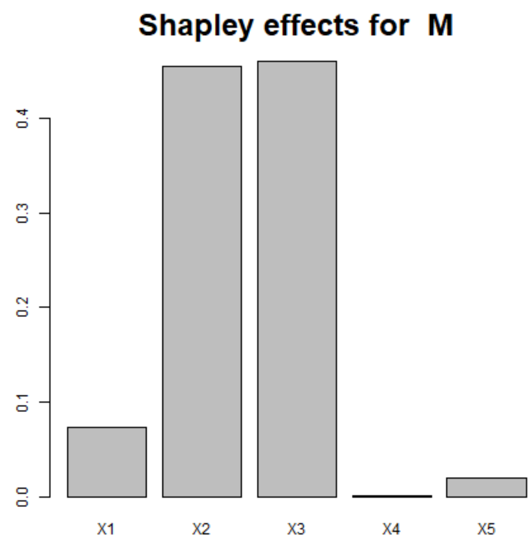


Figure 17: Shapley effects of model M and X1 ~ N(10,2) , X2 ~ N(1, 0.5), X3 ~ N(100, 50), X4 ~ N(1000, 10), X5 ~ N(0.1, 0.01)

7.3 Example III: Nonlinear levelized cost of energy model

Now consider a realistic LCOE model adapted from the recent study of Jadali et al. [99] that compared full and partial decommissioning vs. repowering end-of-life scenarios for a OFFWF with a TEA, which included a MC UA but a OATSA of LCOE. Inputs to SA were AEP, DR, cost of development and consenting (D&C), installation and commissioning costs (I&C), O&M costs, production and acquisition (P&A) costs, partial and full decommissioning costs, and repowering costs (RC). The study included UA with MC simulation but OATSA of LCOE. LCOE was calculated with (15).

The case study focused on a realistic but hypothetical OWF deployed in UK waters. It consisted of a deterministic analysis and stochastic analysis. For the deterministic analysis, the AEP was assumed to be constant and equal to 1734792 MWh/year. The operating time of a OWF is considered 20 years. The stochastic part consisted on MC UA and OATSA of LCOE for partial and full decommissioning and repowering scenarios. For the MC experiment, random sampling was used with the size of N = 100000 iterations. The distributions of variables for the UA in [99] are given in Table 9.

There are no major concerns on the UA part, only that quasi random sampling could be used for in order to reach the same level of accuracy with a significantly less sample size, but the chosen sample size of 100000 is big enough to overcome the inhomogeneity ever present in any random sample. The major shortcoming of SA in [99] is that OAT was used. OAT is a good an example of convenience sampling. It is popular and easy to integrate in any analysis. In [99] the baseline is the deterministic result, but the amount of percent is omitted altogether. The reader is invited to explore what happens to the sample when OATSA is used.

There were seven variables in SA in [99]. By increasing and decreasing the baseline by p% one variable at a time, 14 new points in input space are sampled. So in [99] a sample of 100000 points was used for UA, but a sample of 15 (14 + baseline) points was used for SA. Even without going into the nuances of the calculation procedure, it is obvious that the sample sizes for UA and SA are drastically different, several magnitudes apart to be precise. So how can OATSA results be reliable to make a decision whether to decommission or repower a OFFWF? Tsvetkova & Ouarda [13] argued that the same sample can be used for both UA and global SA. Why not integrate variation in AEP into the sample used for MC experiment and then use the results for SA? That way sample size for UA and SA would be identical

An alternative experiment design is for the repowering case is proposed. The sample size is reduced to 1000, as quasi random sampling is used. The p% for OATSA is assumed to be 10, although the value of p is of little importance, as the underlying sampling for OATSA is not sufficient. The deficiency of the OAT approach is alleviated somewhat by the Morris method [1] that uses a sufficient enough sampling and then from the sampled points assesses the OAT effects on the model. The baseline value of the DR is assumed to be 8%, the distribution for AEP is assumed to be normal (1734792, 173479), and the distribution for the DR - to be normal *N(0.08, 0.02).*

Table 9 : Inputs to levelized cost of energy model

Variable name	**Meaning**	**Distribution**	**Distribution parameters**
D&C	Cost of development and consenting	Normal	*N(205750, 20575) [99]*
P&A	Production & acquisition costs	Normal	*N(1040229, 10422) [99]*
I&C	Installation & commissioning costs	Normal	*N(305742, 30574) [99]*
O&M	Operation & maintanence costs	Normal	*N(56597, 5659) [99]*
RC	Repowering costs	Normal	*N(707035, 70703) [99]*
AEP	Annual energy production	Normal	*N(1734792, 173479)*
DR	Discount rate	Normal	*N(0.08, 0.02)*

The UA results in Figure 18 show a skewness of the LCOE distribution not found in [99]. The UA results are not the focus of this example, but are considered worth mentioning in the context of reasoning and approaching uncertainty.

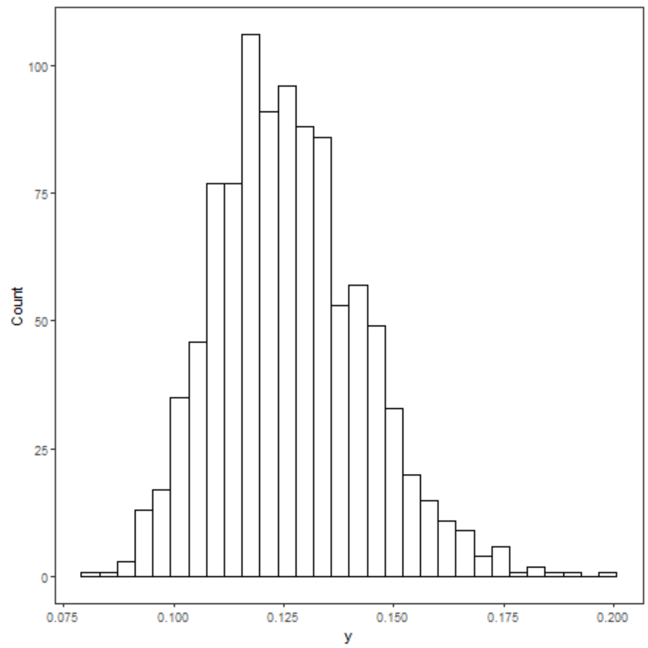


Figure 18 : Uncertainty analysis results for levelized cost of energy model

The results of SA, i.e. the ranking of the inputs according to the degree it influences the variance of LCOE, would be different. The OATSA results in Figure 19 suggest that P&A costs are most influential after the AEP. The scatterplot of LCOE in Figure 20 does not provide clarity on the second most influential factor in this case. The Sobol method (Figure 21) and Shapley effects (Figure 22) identify DR to take the second place and P&A – the third. For this case, surprisingly the difference between OATSA and GSA methods for a nonlinear LCOE model were not as eye-catching as in the previous examples, but one must keep in mind that the LCOE model of Jadali [99] although realistic but is still hypothetical and all distributions are taken with the same value of standard deviation.

The previous simplified examples demonstrated that, although for some cases OATSA results do coincide with GSA results, OATSA if used at all are to be used with extreme caution, as the results are sensitive to the distributions of the inputs.

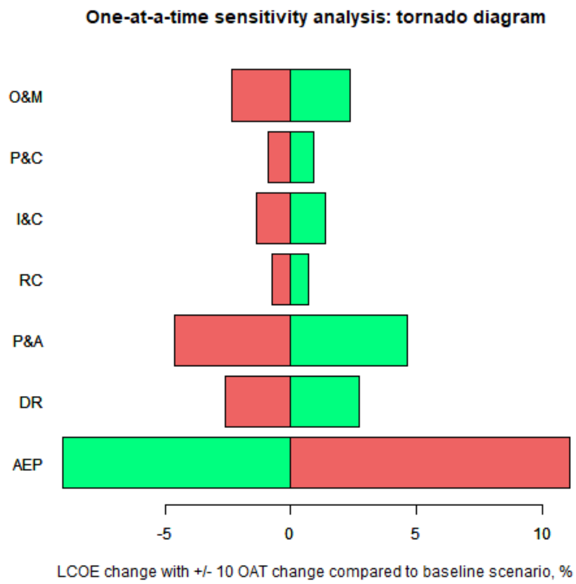


Figure 19 : One-at-a-time sensitivity analysis results for levelized cost of energy model

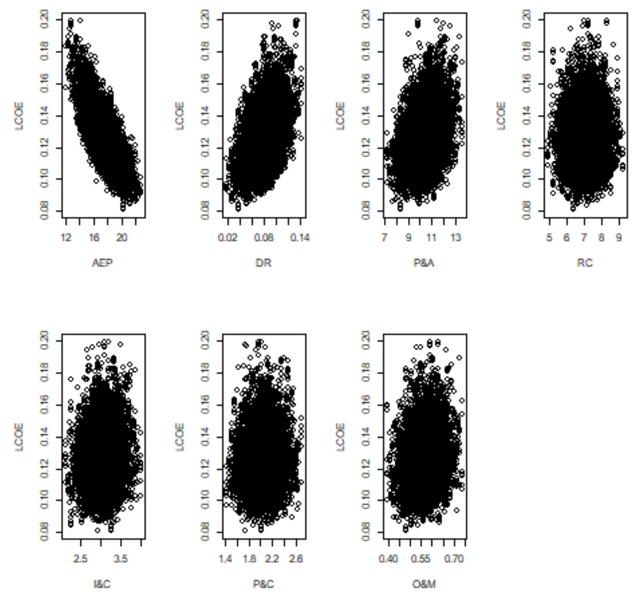


Figure 20 : Scatter plot of levelized cost of energy model

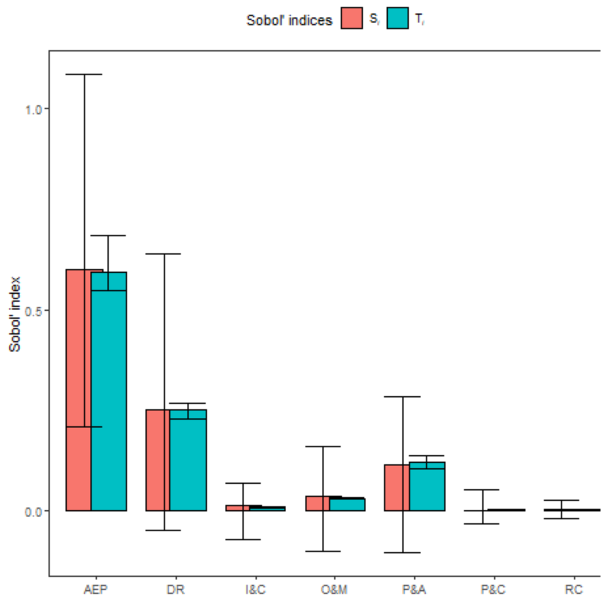


Figure 21 : Sobol indices for levelized cost of energy model

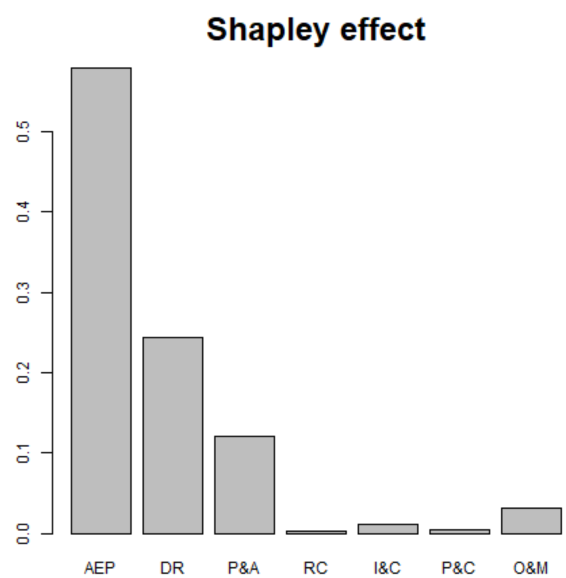


Figure 22 : Shapley effects for levelized cost of energy model

8 Critical synthesis

Section 9 synthesizes critical remarks on the review article pool, observations and generalizations encountered in the process of the review.

8.1 Trends

The trends unveiled in the process of this review are (1) all model commonly used in WRA are nonlinear, (2) OATSA prevails in WRA despite its inapplicability to such models, (3) the more technical WRA study is the more likely for GSA to be employed, (4) GSA is becoming more popular in WRA over time, and, last but not least, (5) policy implications made on unreliable OATSA study results in WRA might lead to dire consequences.

The review summary (*Table 10*) indicates the prevalence of nonLMs and OATSA in WRA. The use of keywords such as a *baseline*, a *change in %,* or a *tornado diagram* indicates OATSA.

Table 10: Summary of the review of sensitivity analysis in wind resource assessment

SA model	Non-linearity of model	Relationship to key inputs	#of articles in review	References of the reviewed articles	OAT SA	GSA
GOFM	Yes	$R^2 = 1 - \frac{\sum_{i=0}^{n}(w_i - v_i)^2}{\sum_{i=0}^{n}(w_i - v_{ave})^2}$	2	[33][34]	100%	0%
WP	Yes	$P = \frac{1}{2}\, C_p \rho A\, w^3$	174	[35][36][37][38][39] [40][41][42][43][44] [45][46][47][48][49][50][56]	53%	47%
WE	Yes	$AEP = \frac{1}{2} 8670\, C_p \rho A w^3$	14	[13][52][53][56][66] [58][59][60][61][62][63] [64][65][67]	71%	29%
NPV	Yes	$NPV = \sum_{i=0}^{N} \frac{AEP_i\, FIT - CAPEX_i - OPEX_i}{(1+r)^i}$	27	[52][60][61][64] [70][71][72][73][74][75][78][77] [79][81][83][84][85][86][87][88] [91][92][93][94][95][96][97]	96%	4%
IRR	Yes	$IRR \sim \sqrt[N]{r}$	14	[52][61] [73][78][81][88][91][96] [101][102][103][104][105][106]	93%	7%
PP	Yes	$PP = \frac{CAPEX}{AEP * FIT - OPEX}$	6	[61][78][84][102][113][114]	100%	0%
LCOE	Yes	$LCOE = \frac{\sum_{i=1}^{N} (CAPEX_i + OPEX_i)/(1+r)^{\mathrm{i}}}{\sum_{i=1}^{N} AEP_i/(1+r)^{\mathrm{i}}}$	39	[52][74][95][99][107] [115][116][117][118][119] [120][122][123][124][125] [126][127][128][129][130][131] [134][132][136][139][140][141] [142][143][144][146][147][148] [173][178][179]	87%	13%
CAPEX	Yes	$CAPEX = -1.485\ 10^{11} P_{WT}^{0.001} + 2.353\ 10^6\ WD + 2.53\ 10^6 D + 2.451\ 10^6\ P_{WF} + 1.487\ 10^{11}$	4	[132][149][151][152]	75	25
OPEX	Yes	$OPEX == -6.349\ 10^8 P_{WT}^{0.187} + 2.595\ 10^{-19} e^{0.83D} +$	5	[53][132][149][151][153]	60	40

		$8.414\ 10^5\ P_{WF} +$ $9.506\ 10^8$				
Average	**100%**		**102**		**82%**	**18%**

8.2 Pitfalls

The review found evidence of the following pitfalls of SA to be present in WRA:

(1) Lack of universal definition of SA in WRA;
(2) Interchangeability of SA and UA;
(3) Disregard to the lack of applicability of OAT method to nonLMs;

The need for a clear standard definition of SA in Earth sciences was voiced by Razavi et al. [161]. The motivation behind SA can be diverse. Saltelli et al. [4] provide examples of SA objectives, i.e. to find errors in the model, prioritize research activities, and *"identify critical regions in the space of inputs"* [4]. In some studies, no clear motivation (research questions for SA) was found [46][102]. Often no ranking of SAIVs was established after a SA was performed [84][102], which is attributed to the lack of a clear research question. Sometimes SA is used to identify which variables have a positive and a negative effect on the model, for example [139][142]. SA is also used to make inferences about the dependency of SAIVs and SAOV [62][144]. Examples of interchangeability of the terms UA and SA were detected in [14][117][121]. Tran et al. [117] presented the PDFs of LCOE as GSARs, when, in fact, they are UA results. Ayodele et al. [14] in an encyclopedia review article of methods for UA of WT output uses UA and SA interchangeably. Heck et al. [121] reasonably argues in favor of a MC approach for integrating uncertainty into LCOE, he states that "*if uncertainty is included at all, it is usually through a simple sensitivity analysis that uses high/low values for each variable to estimate upper and lower bounds on the LCOE*" [121]. With this statement, he shows the common understanding of uncertainties or the interchangeability of UA and SA. Only a handful of studies accounted for the nonlinearity of the models common for WRA [13][36][37][39] [42][52][53][118][120]. The rest disregarded model nonlinearity and used OATSA.

9 Conclusion and outlook

The review findings of common SA practices in the field of WRA greatly correspond with those of Morras Bora et al. [120] in offshore wind and Menberg et al. [203] but in the field of building energy models. Building energy models, like the models used in WRA, are nonlinear [204], and GSA is computationally expensive while it provides stable results [205]. In WRA, computational burden for the WRA models mentioned in this review is not an issue (except for the offshore cost model [120]), although it is one for WRF and CFD models [13].

The definition and purpose of SA in WRA is often misconstrued in a number of ways. A universal definition of SA in the field is absent. This discrepancy in terminology causes discrepancy in motivation, misunderstanding in the research questions SA addresses and goals SA could help achieve (Section 8 for details). This finding corresponds with the those of [4][161]. In Section 2, the most common SA outputs among variables of interest used in WRA have been identified as GOFM, WP, WE, NPV, IRR, PP, LCOE, CAPEX, and OPEX. All were shown to be nonlinear. OATSA is popular mainly due to its convenience but not credibility. Moreover, OATSA has been previously shown to be unsuitable for nonlinear models [20]-[22]. Nonetheless, it is flourishing by dominating among other SA methods in the field of WRA with prevailing nonlinear models. 53-100% of articles reviewed in each category (82% on average, *Table 10*) used OATSA. Despite its unreliability, policy implications were made based on results of OATSA of LCOE [105][138], which is a call for serious concern. To make matters worse, professional software designed for renewable energy assessment, such as RETScreen [68], is promoting the use of unreliable OATSA as a tool for reasoning about uncertainty and risks associated with investing in wind energy.

Section 5 Geography found based on the number of SA studies in the literature that LCOE is the most popular model in WRA, and that the UK, the US and China are the most studied countries. Offshore wind is of special significance to the UK and Spain. The costs of offshore wind has been dropping in the last years, making the more abundant offshore wind potential feasible for integrating into the grid. Profitability assessment of the next generation of OFFWFs require complex nonlinear techno-economic models that capture the new relationships formed due to rapid technological advancement and policy incentives [120]. Borras Mora et al. [120] call GSA necessary to study these complex models, as relationships between inputs and outputs are poorly understood [120]. The significance of GSA for decision support in policy in general was emphasized in [7]. Yet the voice in favor of GSA remains unheard, despite the abundancy of available open source software tools for GSA. A combination of MC UA but OATSA was found in a number of reviewed articles [76][86][94][95][99], while GSA could have been applied at no additional computational cost [13]. It demonstrates that OAT is mostly used out of habit.

When GSA was found to be used in WRA [13][36][37][39] [42][52][53][118][120], the most common GSA method was the variance-based Sobol method, the least common – Shapley effects [54] and PAWN [6]. Section 7 focused on the specifics of application and discussed three examples illustrating that OATSA can even be misleading for a LM, let alone nonLMs, as SA results depend on the model, the distributions of the inputs, and interactions among the factors. It also showed that although OATSA results do coincide with GSA results in some particular cases, OATSA if used at all should be used with extreme caution, as SA results are sensitive to the distributions of the inputs.

Future research should focus on GSA in WRA. Notably, not one GSA study of GOFMs and PP in WRA was detected. The limited amount of studies dealing with SA of GOFMs indicates a necessity for GSA of GOFMs. Calculating Shapley effects [54] for factors contributing to NPV and/or LCOE (as the most popular economic SAOVs used in FS's) for ONWF and OFFWF (especially for FOFFWFs as it is one the hot topics in WE) would be ground-breaking. Martin [153] defined most influential factors for O&M cost of a OFFWF and suggested refining their distributions and running a "*more sophisticated GSA in order to quantify the amount of sensitivity*" [153], so applying Sobol, Shapley or PAWN to this experimental design is of justified importance. Mytilinou et al. [149] suggest increasing the sample size of MC simulation to study the higher order interdependencies, this can be done with total effect Sobol SI's. Also, [137] suggested studying "*sensitivity of LCOE of OFFWFs to the years in which each of the different costs occur*" [137].

Declaration of competing interest

There is no conflict of interest regarding this publication.

CRediT authorship contribution statement

Olga Tsvetkova: Conceptualization, Methods, Writing - Original draft preparation. **Taha B.M.J. Ouarda**: Funding acquisition, Supervision, Writing - Reviewing and Editing.

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