Improving investigation of wind turbine optimal site matching through the self-organizing maps

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Abstract

A wind turbine (WT) site optimization procedure was developed and applied on two different onshore and one offshore sites, supplied with tall met masts and belonging to exemplary wind climates. In addition to detecting the most suitable WT for each site, Kohonen's self-organizing maps (SOMs) were employed to improve investigation of those parameters mostly influencing site optimization. Three years (2013–2015) of 1-h vertical observations from local met masts and a database of 377 onshore and 23 offshore commercial WTs were used.

As a result, maximizing capacity factor (CF) was confirmed as a *good* objective function, though not the *best*, which was minimizing levelized cost of energy ($LCoE$). In general, these two conditions do not necessarily match: variously setting WT parameters may either result in an $LCoE$ reduction or CF increase, but both conditions do not occur concurrently. A key finding was that minimum $LCoE$ cannot be achieved by indefinitely increasing the WT hub height, but rather through detection of an optimum value obtained as a unique solution of the optimization procedure. Furthermore, the capability of SOM to recognise the cluster structure of all parameters influencing WT site optimization shed further light on their mutual relationship, thus proving to be an ideal tool

27 to address the non-convex nature of this issue.

28

29 *Keywords:*

30

31 Optimal site matching; Wind resource vertical profile; Wind turbine database; Capacity factor (CF);

32 Levelized cost of energy (LCoE); Self-organizing map (SOM)

33

Nomenclature

Abbreviations

WT	wind turbine
PL	power law
ASL	above sea level
ANN	artificial neural network
SOM	self-organizing map
MinLCoE	minimum levelized cost of energy
MaxCF	maximum capacity factor
TR	top-right
BR	bottom-right
TL	top-left
BL	bottom-left

Variables

v	wind speed [m/s]
z	height of observations [m]
α	wind shear exponent [–], Eq. (2)
c	Weibull scale factor [m/s]
k	Weibull shape factor [–]
v_m	mean wind speed [m/s]
v_{median}	median wind speed [m/s]
v_{mp}	most probable wind speed [m/s], Eq. (4)
v_{me}	wind speed carrying maximum energy [m/s], Eq. (5)
ρ	air density [kg/m ³], Eq. (7)

60	P_{atm}	atmospheric pressure [mbar]
61	T	air temperature [K]
62	P	wind power density [W/m^2], Eq. (9)
63	E_a	wind energy generated by an ideal WT [MWh/y], Eq. (11)
64	H_{hub}	WT hub height [m]
65	P_r	WT rated power [kW]
66	E_r	WT rated energy [MWh/y]
67	D	WT rotor diameter [m]
68	A	WT rotor diameter area [m^2]
69	v_i	WT cut-in wind speed [m/s]
70	v_r	WT rated wind speed [m/s]
71	v_o	WT cut-off wind speed [m/s]
72	Φ	WT design ratio [–], Eq. (17)
73	η_r	WT rated efficiency [–], Eq. (18)
74	β	intensity ratio [–], Eq. (19)
75	v_r/c	normalized rated speed [–], Eq. (20)
76	η_T	WT energy efficiency [–], Eq. (21)
77	A_{WT}	WT availability [%], Eq. (16)
78	AEY	annual energy yield [MWh/y], Eq. (14)
79	CF	capacity factor [%], Eq. (15)
80	$LCoE$	levelized cost of energy [\$/MWh], Eq. (22)
81	$C_{initial}$	initial capital cost (capital expenditure) [\$], Eq. (23)
82	C_{WT}	WT capital cost [\$], Eq. (24)
83	C_i	annual cost (operational expenditure) at year i [\$/kW/y]

84

1. Introduction

Wind energy optimal site matching deals with the best pairing between a given site and a selected range of WTs [1]. This involves wind engineers or WT manufacturers in analysing and determining, during the planning stage of a wind energy project, which type of WTs is most suitable for a given site, or vice versa [2]. In the past literature, several criteria have been proposed to implement this pairing procedure. One of the most popular because of its simplicity, for example, is the one developed by Jangamshetti and Rau [3], based on identifying the optimum WT performance index curve, obtained from the WT normalized power curves, so as to yield higher energy production at a higher capacity factor. In fairness, a common issue affecting the latter and most of similar studies is the tendency to simplify, by implementing various models, the characteristics of either the site or WTs, or even both. Indeed, various shortcomings may be recognised in their approach, including: (i) site's wind speed vertical profile is neglected [1–8]; (ii) a very small number of WTs, not sufficiently representative of the commercial market (as shown, e.g., by Carrillo et al. [9]), is considered [3,5,7,8,10–13]; (iii) manufacturer WT power curves are not explicitly treated but just fitted by means of polynomial, exponential, cubic or quadratic expressions [1–3,8,12,14]; (iv) capacity factor (or an index being a function of it) is taken as the unique optimization parameter [1–3,7,11]; (v) applications on offshore locations are numbered (with rare exceptions such as, e.g., [5,7,15]).

Actually, a key issue is to turn “optimization” from a theoretical into a practical meaning, and thus to assign it a clear and unambiguous definition through recognition of the parameter required to be “optimized”, i.e. the objective function [6]. Taking this into consideration, the capacity factor alone cannot provide overall information on WT characteristics, as further parameters such as WT efficiency should also be taken into account [10]. On the other hand, economic viability of a wind energy project is a key factor to be considered when installing a wind farm [16], and thus a cost optimization should necessarily be accomplished, as demonstrated, e.g., by [4,5,12–14,17–20]. To

111 this aim, the levelized cost of energy – rather than the capacity factor – proved to be the most robust
112 objective function as it appropriately describes the potential profitability of a wind energy project
113 [13,21]. A popular cost reduction technique is to increase the WT rated power by making WTs larger.
114 However, as noticed by Ashuri et al. [20], it is not clear whether further WT upscaling beyond the
115 existing 5–7 MW range is both technically feasible and economically attractive: the advantage of
116 upscaling is the increase in energy yield, while its disadvantage is the increase in initial capital cost.

117 This study intends to take a step forward in optimal site matching, paying specific attention to
118 practical wind energy issues. Therefore, sites' features were thoroughly assessed by constructing
119 wind resource vertical profiles, while WTs characteristics were not modelled, but rather explicitly
120 treated. Furthermore, instead of maximizing capacity factor (yet retained for comparison),
121 minimizing levelized cost of energy was the adopted objective function. The goal of this study is
122 twofold: (i) to detect the most suitable WT for each site among all commercially available WTs and
123 analyse the issues behind; (ii) to shed further light, via the use of the self-organizing maps (SOMs),
124 on those WT parameters mostly influencing site optimization. In recent years, Kohonen's SOMs
125 [22] have been successfully applied in various scientific disciplines to recognize complex patterns
126 and find hidden structures in high-dimensional datasets. In wind energy studies, SOMs have been
127 applied, e.g., in daily electric load profile forecasting [23], wind power forecasting [24,25], wind
128 speed spatial interpolation [26], WT performance assessment [27], and WT fault diagnosis [28]. To
129 the best of the Author's knowledge, although the strongly non-convex nature of WT site
130 optimization, the use of the SOMs has never been applied to address this issue yet.

131 Two different onshore and one offshore sites, each with a tall met mast installed, have been
132 considered: a flat and sea-level inland site (Cabauw), an elevated mountain site with fairly complex
133 terrain (Boulder), and an open-sea offshore platform (FINO3). Three years (from 01/01/2013 to
134 31/12/2015) of 1-h observations of wind speed, air temperature, and atmospheric pressure collected
135 at various heights from local met masts have been used. An extensive database including 377
136 onshore and 23 offshore commercial WTs has also been used.

137

138 **2. Methods**

139

140 *2.1 Wind speed vertical extrapolation*

141 The PL is the most widely used wind speed extrapolating model for wind energy studies since it
 142 is the most accurate as well as the simplest [29]. According to the PL, surface wind speed is
 143 vertically extrapolated as [30]:

$$144 \quad v_2 = v_1 \left(\frac{z_2}{z_1} \right)^\alpha \quad (1)$$

145 where v_1 and v_2 are wind speeds at heights z_1 and z_2 , respectively. The PL is an empirical model best
 146 fitting wind speed profiles up to 300 m from the ground [29]. From Eq. (1), α can be measured once
 147 concurrent records of v_1 and v_2 are available:

$$148 \quad \alpha = \frac{\ln(v_2 / v_1)}{\ln(z_2 / z_1)} \quad (2)$$

149

150 *2.2 Site's wind energy characteristics*

151 Since best fitting real wind speed data (e.g. [31]), the two-parameter Weibull probability density
 152 function $f(v)$ is commonly used to express wind speed frequency distribution and estimate wind
 153 power density [32]. It is defined as:

$$154 \quad f(v) = \frac{k}{c} \left(\frac{v}{c} \right)^{k-1} \exp \left[- \left(\frac{v}{c} \right)^k \right] \quad (3)$$

155 where c is the scale parameter, and k the shape parameter. Once c and k have been estimated (e.g.
 156 based on [33]), meaningful wind speed characteristics can be calculated, such as the most probable
 157 wind speed [10]:

$$158 \quad v_{mp} = c \left(\frac{k-1}{k} \right)^{1/k}, \quad (4)$$

159 and wind speed carrying maximum energy [10]:

$$v_{me} = c \left(\frac{k+2}{k} \right)^{1/k} \quad (5)$$

For an area A of the WT rotor disc and a given wind speed v , site's available wind power is [34]:

$$P(v) = \frac{1}{2} \rho A v^3 \quad (6)$$

where ρ is the air density, which may be calculated as [35]:

$$\rho = \frac{P_{atm}}{R \times T} \quad (7)$$

with P_{atm} the atmospheric pressure [mbar], R the specific gas constant for air [287.053 J/kg K], and T the air temperature [K].

When elevated P_{atm} is not available, the P_{atm} vertical profile may be approximated by [36]:

$$P_{atm}(z) = P_0 \cdot \exp[-(0.0342/T) \cdot z] \quad (8)$$

where P_0 is the atmospheric pressure at ground level [mbar].

Integrating $P(v)/A$ over all possible wind speeds multiplied by the fraction of time each wind speed is experienced, from Eq. (6) site's wind power density P based on Weibull probability density function can be expressed as [10]:

$$P = \frac{1}{A} \int_0^{\infty} P(v) f(v) dv = \frac{1}{2} \rho c^3 \Gamma\left(\frac{k+3}{k}\right) \quad (9)$$

where Γ is the Gamma function.

2.3 Wind energy output

The mechanical power $P_m(v)$ extracted from site's available wind power is [37]:

$$P_m(v) = C_p P(v) = \frac{1}{2} C_p \rho A v^3 \quad (10)$$

where C_p is WT power coefficient, whose theoretical maximum value (0.593) is the Betz limit [38].

Wind energy generated by an ideal WT over a period $\bar{t}$ can be calculated as [34]:

$$E_a = \bar{t} \int_0^{\infty} P_m(v) f(v) dv = \bar{t} C_p \int_0^{\infty} P(v) f(v) dv \quad (11)$$

182 with C_p equal to the Betz limit (0.593).

183 The electric power output $P_e(v)$ of an actual WT is given by [6,39]:

$$184 \quad P_e(v) = \eta_m \eta_e P_m(v) = \frac{1}{2} C_p \eta_m \eta_e \rho A v^3 \quad (12)$$

185 where η_m and η_e are the efficiencies of mechanical transmission and electric generation [6].

186 For WTs operating at constant P_r with maximum efficiency between v_r and v_o , the relation
187 between $P_e(v)$ and the available wind speed v can be mathematically approximated by [37]:

$$188 \quad P_e(v) = \begin{cases} 0 & , 0 \leq v < v_i \\ (a + bv + cv^2)P_r, & v_i \leq v < v_r \\ P_r & , v_r \leq v < v_o \\ 0 & , v > v_o \end{cases} \quad (13)$$

189 where the constants a , b , and c are functions of v_i and v_r , as provided, e.g., in [37].

190 Combining Eqs. (12) and (13), actual energy production (E) of a WT over a 1-year period ($\bar{t}$
191 =8760 hours), or AEY , is [10]:

$$192 \quad AEY = E = \bar{t} \int_0^{\infty} P_e(v) f(v) dv = \bar{t} \int_0^{\infty} \eta_m \eta_e P_m(v) f(v) dv = \bar{t} P_r \int_{v_i}^{v_r} (a + bv + cv^2) f(v) dv + \bar{t} P_r \int_{v_r}^{v_o} f(v) dv \quad (14)$$

193 Capacity factor CF is the ratio of AEY to the energy (E_r) that the WT could have produced if
194 operated at its rated power over the same period [34]:

$$195 \quad CF = \frac{E}{E_r} \quad (15)$$

196 WT availability A_{WT} is defined as [37,40]:

$$197 \quad A_{WT} = MTBF / (MTBF + MTTR) \quad (16)$$

198 where $MTBF$ is the mean time between failures and $MTTR$ the mean time to repair. In a wind farm
199 reliability analysis, availability is a key measure of performance as it is closely related to energy
200 production and revenues [41].

201 202 2.4 Wind turbine design and "paired" parameters

203 In the past studies, crucial parameters have been introduced to classify WT characteristics, as

204 well as to assess on-site WT performances once paired with site's characteristics.

205 WT design parameters include the WT design ratio [6]:

206
$$\Phi = v_r/v_i, \quad (17)$$

207 and WT rated efficiency [6,10]:

208
$$\eta_r = \frac{P_r}{(1/2)\rho A v_r^3} \quad (18)$$

209 "Paired" parameters (i.e. between WT and site) include the intensity ratio [6]:

210
$$\beta = v_m/v_i, \quad (19)$$

211 the normalized rated speed [3]:

212
$$v_r/c, \quad (20)$$

213 and WT energy efficiency, i.e. the ratio between actual WT energy output (*AEY*) and wind energy
214 generated by an ideal WT (*E_a*) [10]:

215
$$\eta_T = \frac{AEY}{E_a}. \quad (21)$$

216

217 2.5 Cost estimation

218 The cost of a wind farm project varies significantly over time and location, generally depending
219 on the number of WTs, the distance of the site from the WT manufacturer, land leasing,
220 foundations, planning and licensing, grid connection, distribution system, etc. [34]. A careful
221 evaluation of all these components spanning the entire project's lifetime should therefore be
222 performed. Due to the large number of WT models employed, in this study an exact cost evaluation
223 for each WT appeared unfeasible, vice versa, as well as an evaluation of the entire wind power
224 project (wind farm layout optimization), which on the other hand is beyond the scope of the work.
225 Therefore, a simplified approach for estimating each project's component was adopted. In addition,
226 cost parameters have been estimated taking the 2016 US market as a reference and [\$] as currency.

227 The levelized cost of energy (*LCoE*) is recognised as the economic "figure-of-merit" most
228 commonly used to rank the economic viability of a wind energy project [42]. It represents the sum

of all costs of a fully operational wind farm over the project's lifetime with financial flows discounted to a common year [43]. $LCoE$ for a wind energy project is calculated as [13]:

$$LCoE = \frac{C_{initial} + \sum_{i=1}^n C_i / (1 + d)^i}{\sum_{i=1}^n AEY / (1 + d)^i} \quad (22)$$

where $C_{initial}$ is the initial capital cost (capital expenditures), C_i the annual cost at year i (operational expenditures), i the year since installation, n the operational life, and d [%] the interest rate of the investment.

The initial capital cost $C_{initial}$ of a wind farm project is the sum of the WT capital cost (C_{WT}), the balance of system, and financial costs [44]. In general, C_{WT} can be considered as a quite constant fraction (p) of $C_{initial}$. In their extensive review on the US market for the year 2013, Moné et al. [44] reported C_{WT} to account for 68% of $C_{initial}$ for onshore, and 32% for offshore projects. Therefore, using these percentages (p) for onshore (68%) and offshore (32%) projects, $C_{initial}$ can be approximated as:

$$C_{initial} = C_{WT} / p \quad (23)$$

It is clear that, as also noted by Snel [45], for offshore locations the use of Eq. (23) leads to higher uncertainties in the $C_{initial}$ computation than for onshore locations, as at offshore locations it is the balance of system (including foundation, installation and electrical cable costs) to play the major role in the cost (52% in US, according to Moné et al. [44]).

To calculate C_{WT} , the parametric approach by Perkin et al. [13] was applied, who expressed C_{WT} as an increasing function of P_r , D and H_{hub} . Relying on the WT design cost and scaling model developed by Fingersh et al. [46], based on the 2002 US market, Perkin et al. [13] proposed a single C_{WT} expression obtained by fitting the 24 cost equations (one for each WT component) developed by Fingersh et al. [46]. The C_{WT} expression, detailed as Eq. (9) in Perkin et al. [13], is in the form:

$$C_{WT} = f_i * f(P_r, D, H_{hub}) \quad (24)$$

where f_i is an inflation scaling factor (equal to 1.34) accounting for the US average inflation rate between 2002 and 2016. Of course, Eq. (24) is a more refined expression for C_{WT} than those (e.g.

254 [8]) only relating C_{WT} to P_r .

255 Annual costs C_i , generally including operation and maintenance costs, have been derived from
256 Moné et al. [44] as 50 [\$/kW/y] for onshore and 136 [\$/kW/y] for offshore projects.

257

258 2.6 Self-organizing map

259 The SOM is the result of the converged SOM algorithm, which is a type of unsupervised
260 learning ANN-based model that implements a nonlinear projection from a high-dimensional space
261 of sensory or other input signals onto a low-dimensional (usually two-dimensional) regular grid (or
262 lattice) of neurons [47]. The SOM converts complex, nonlinear statistical relationships between
263 high-dimensional data into simple geometric relationships on a low-dimensional display [22]. Each
264 neuron on the two-dimensional grid also has a d -dimensional weight (or prototype) vector, where d
265 is the dimension of the input vectors. Thus, SOM defines a nonlinear projection from the d -
266 dimensional data space to the two-dimensional grid [48]. Mapping from the original data space to
267 the grid of neurons is accomplished in an orderly fashion while preserving the most important
268 topological and metric relationships of the primary data [47]. This means that data vectors close to
269 each other in the data space tend to map to the same or close-by neurons in the grid. This makes
270 visualization of the grid useful in exploring the relationships of variables and the possible cluster
271 structure of the data [48].

272 The core of the SOM algorithm is the learning rule stated by Kohonen, which allows the
273 topographic map to organize itself [49]. The algorithm defines an iterative training process where
274 each input neuron is connected to all output neurons. Before the training, the data vectors have to be
275 normalized such that the mean of each variable is 0 and the variance is 1: this normalization method
276 scales the data linearly, which preserves the structure of the absolute values of the measurements
277 [50]. After initializing the neurons with values spanning the space of two dominant eigenvectors,
278 the training proceeds in two alternating steps. Data vectors are first mapped to neurons by looking
279 for the best-matching unit (or the winner neuron, i.e. the neuron with the closest prototype vector)

280 using a Euclidean distance measure between the data vector and the set of neurons. Second, the
281 neurons are adapted to better represent the distribution of the data [50], and thus connected to
282 adjacent neurons by a neighbourhood function which determines the rate of change (i.e. the strength
283 of adaptation) of neighbouring neurons around the winner neuron [48]: this function dictates the
284 topology, or structure, of the map [51]. Typical neighbourhood functions are Gaussian, Cut
285 Gaussian, bubble, and Mexican hat [51]. This learning procedure is controlled by another two
286 parameters, both decreasing monotonically with the training steps: the learning rate and the
287 neighbourhood radius. The learning rate, comprised between 0 and 1, specifies to what degree the
288 neurons generally adapt to a given input vector, while the neighborhood radius determines to what
289 degree neighborhood neurons adapt depending on their distance to the winner neurons [22]. For the
290 latter, an initial value higher than half the lattice's diameter is recommended [51].

291 In the case of a 2-dimensional grid, the neurons of the map can be arranged either on a hexagonal
292 or a rectangular lattice; the use of hexagonal lattice is usually recommended because all 6
293 neighbours of a neuron are at the same distance (as opposed to the 8 neighbours in a rectangular
294 lattice): this way the maps become smoother and more pleasing to the eye [51]. To assess whether
295 the map has properly adapted itself to the training data, thus helping choose suitable parameters,
296 two quality measures are commonly used: (i) the quantization error, measuring how good the map
297 can fit the input data, and (ii) the topographic error, measuring how well topology is preserved by
298 the map.

299

3. Sites and observations

Two onshore and one offshore sites have been considered (Table 1): Cabauw (Netherlands), a flat and sea-level inland site supplied by a 213-m mast; Boulder (CO, USA), an elevated mountain site affected by a fairly complex terrain and supplied by the 82-m M2 mast; FINO3, an offshore platform 80 km off the coast in the North Sea (Germany) supplied by a 120-m mast. These sites are real cases approximately falling into three out of six exemplary wind climate sites as defined by Fuglsang et al. [5]. A detailed description of their characteristics may be found, e.g., in [30] for Cabauw, [52] for Boulder, and at <http://www.fino3.de> for FINO3.

Table 1

Characteristics of the met mast supplied application sites being investigated.

Location (State, Country)	Operator	Latitude (deg N)	Longitude (deg E)	Altitude (m ASL)	Terrain, and land use
Cabauw (Netherlands)	KNMI	51° 58' 25"	4° 55' 55"	−0.7	Flat, open pasture, 50 km from the coast
Boulder (CO, USA)	NWTC	39° 54' 38"	−105° 14' 5"	1855	Fairly complex, hills with no trees
FINO3 (Germany)	BSH	55° 11' 42"	7° 9' 30"	0	Offshore, 80 km off the coast

A 3-year (01/01/2013–31/12/2015) observation dataset including 1-h wind speed, air temperature, and atmospheric pressure have been used. Table 2 reports, for each mast, the available sensor heights for each variable and their valid record percent.

Table 2Features of met masts and 1-h data samples (2013–2015)^a.

Site	Mast height (m)	Variable	Sensor heights (m)	Valid records (%) ^b
Cabauw	213	Wind speed	10, 20, 40, 80, 140, 200	98.08
		Temperature	10, 20, 40, 80, 140, 200	
		Pressure	0	
Boulder	82	Wind speed	10, 20, 50, 80	98.95
		Temperature	2, 50, 80	
		Pressure	0	
FINO3	120	Wind speed	50, 60, 70, 80, 90, 100	82.49
		Temperature	29, 55, 95	
		Pressure	23, 94	

^a Statistics for 26,280 1-h records over the period 01/01/2013–31/12/2015.^b Concurrent valid records are considered for all variables and all sensor heights.

4. Wind turbine database

A total of 400 (377 onshore and 23 offshore) commercial WTs have been considered. Where they were not directly available from the manufacturers' official websites, WT characteristics have been obtained from the WindPower database [53]. All wind energy yield computations have been performed by using an updated version of the wind resource assessment tool described in [54], where the 400-WT database was implemented.

A summary of main WT characteristics is provided by the histograms plotted in Fig. 1. Further WT characteristics are shown in Figs. S1 and S2 of the supplementary material provided.

In order to assess availability A_{WT} , all analysed WTs have been grouped into four populations of WT systems: (A) fixed-speed; (B) variable-speed with induction generator; (C) variable-speed with doubly fed induction generator; (D) variable-speed with direct-drive synchronous generator. Thus, depending on WT system, availability values have been assumed as: (A) 99.8%; (B) 98.6%; (C) 98.8%; (D) 99.9%. As for systems (A–C), A_{WT} values have been taken from [55], while for systems (D) they have been derived from [56].

Overall, application of Eq. (24) returned for the C_{WT}/P_r ratio a range of 950–4,200 \$/kW (averaging 1,520 \$/kW) for onshore WTs, and 1,080–3,275 \$/kW (averaging 1,560 \$/kW) for offshore WTs. The reliability of Eq. (24) has been roughly assessed after comparison with some updated outcomes from the literature. Onshore, for example, for WTs with P_r ranging 1.8–2.0 MW an average C_{WT}/P_r of 1,320 \$/kW was achieved, being slightly higher than the 1,185 \$/kW value reported by Moné et al. [44] in US (year 2013) for land-based reference projects using 1.91 MW WTs; offshore, for WTs with P_r between 3.6 and 5.0 MW an average C_{WT}/P_r of 1,420 \$/kW was achieved, slightly lower than the 1,660 \$/kW value reported by Moné et al. [44] for offshore reference projects in US (year 2013) using 4.3 MW WTs. A further thorough comparison, performed against market prices, resulted in C_{WT} estimates only slightly lower than costs reported, e.g., for some WTs by Boudia and Guerri [57]: 940 k\$ for Nordex N50-800 (vs. 970 k\$); 1,170 k\$ for Neg-Micon 60-1000 (vs. 1,315 k\$); 1,720 k\$ for Vestas V66-1.65 (vs. 2,000 k\$), and 3,300 k\$ for Vestas V90-3.0 (vs. 3,600 k\$).

Fig. 1. Histograms of the main characteristics of all onshore and offshore WTs analysed: (a) hub height; (b) rated power; (c) rotor diameter; (d) rated wind speed.

5. Search for wind turbine optimal site matching

5.1 Application details

WT optimal site matching has been addressed targeting two objective functions: minLCoE, and maxCF. Fig. 2 shows the flowchart of the implemented optimization procedure.

Fig. 2. Flowchart of the WT optimal site matching procedure.

For each location, the following phases were employed: (i) construction of 1-h z -step vertical profiles of v , ρ and P ; (ii) for each z step, computation of site's annual wind resource and wind energy characteristics (v_m , v_{median} , v_{mp} , v_{me} , c , k , ρ and P); (iii) for each z step, computation of annual paired, energy output and cost parameters by employing all WTs with H_{hub} approximating z ; (iv) for

each z - H_{hub} pairing, selection of the two WT achieving minLCoE and maxCF, and compilation of the two respective z -varying lists of candidate WTs; (v) final detection, across the whole vertical profile of candidate WTs, of the unique WT minimizing $LCoE$ and of the one maximizing CF . Therefore, search for site optimization was a 2-phase stepwise procedure aimed at detecting, for each objective function: (i) a vertical profile of candidate WTs; (ii) the unique WT solution of the optimization procedure among all candidate WTs. Thus, each objective function was applied twice.

Considering the H_{hub} values of the available WT database (Fig. 1a), z ranged from 10 to 160 m for the onshore sites, and from 50 to 150 m for the offshore site. A common step of 2 m was used in z variation for vertical profiling. In the H_{hub} -to- z vertical approximation, a maximum tolerance of ± 2 m between H_{hub} and z was set for the onshore sites, and ± 5 m for the offshore site.

Vertical profiles were constructed based on 3-year 1-h records collected at the available sensor heights (Table 2). At heights where information was not available variables were vertically interpolated/extrapolated for each hour: wind speed profiles were calculated through the PL (Eq. 1) using α values measured each hour between the nearest heights (Eq. 2); ρ profiles, needed to calculate P profiles via Eq. (9), were derived using Eq. (7) after linearly interpolating T , while P_{atm} was vertically extrapolated using Eq. (8) as a function of P_{atm} at the lowest sensor height (P_0). For heights above the highest available sensors (at Boulder and FINO3), wind speed profiles were extrapolated using the same α values of the lower-range wind speed profiles, while T profiles were extrapolated using the same gradients of the lower-range T profiles.

In wind energy computations, for each site WT total power losses (Table 3) have been accounted, based on the approach described in [32,35], as a combination of: (i) WT-specific losses (for gearbox, generator, converter, and unavailability & repair); (ii) site-specific losses (for electric grid connection and icing). As for (i), losses were varied by WT system, with values retrieved from [55] (systems A–C), and from [58] (systems D).

Table 3

Losses (%) by WT system accounted for energy yield calculations at each site^{a,b}.

	Site											
	Cabauw				Boulder				FINO3			
	WT system											
	A	B	C	D	A	B	C	D	A	B	C	D
Gearbox	4.0	3.0	3.0	0.0	4.0	3.0	3.0	0.0	4.0	3.0	3.0	0.0
Generator	2.5	2.2	1.5	3.5	2.5	2.2	1.5	3.5	2.5	2.2	1.5	3.5
Converter	0.0	2.4	0.8	4.7	0.0	2.4	0.8	4.7	0.0	2.4	0.8	4.7
Unavailab. & repair	0.2	1.4	1.2	0.1	0.2	1.4	1.2	0.1	0.2	1.4	1.2	0.1
Grid connection	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0	2.0	2.0	1.0
Icing	3.0	3.0	3.0	3.0	5.0	5.0	5.0	3.0	3.0	3.0	3.0	3.0
Other	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	10.30	12.33	10.07	11.74	12.15	14.14	11.93	13.56	11.20	13.22	10.98	12.63

^a Losses due to gearbox, generator, converter, and unavailability & repair are varied based on WT system: their values are taken from [55] (systems A–C), and from [58] (systems D).

^b Since the study is focussed on single WTs, array losses were not considered.

For each WT, *LCoE* was calculated based on the simplified approach described in section 2.5, where the following was set in Eq. (22): $n=20$ years; $d=5\%$.

Tables 4 and 5 summarize the statistics of WT optimal site matching. For all locations, annual average vertical profiles of wind speed Weibull distributions (Fig. 3), site's characteristics (Figs. 4a, 5a, and 6a), and optimization conditions (Figs. 4b, 5b, and 6b) are presented. Annual vertical profiles of WT design parameters (Φ and η_r) and paired parameters (β , v_r/c and η_T) by optimization condition are also shown in supplementary material (Figs. S3, S4, and S5).

Fig. 3. Height variation of annual wind speed Weibull distributions profiled 2013–2015 at: (a) Cabauw; (b) Boulder; (c) FINO3. Height-related distributions corresponding to WTs achieving minLCoE (red) and maxCF (green) and their power curves are also shown (see Table 5).

Table 4Statistics of the optimal site matching at the three selected sites using single WTs (2013–2015)^{a,b,c}.

Parameter	Site					
	Cabauw		Boulder		FINO3	
	Mean	Range	Mean	Range	Mean	Range
Site characteristics						
z (m)		10–160		10–160		50–150
α	0.243	0.203–0.267	0.106	0.100–0.133	0.098	0.041–0.124
v_m (m/s)	6.76	4.24–8.15	4.70	3.61–5.21	10.36	9.71–10.98
v_{median} (m/s)	6.50	3.76–7.95	3.69	2.78–4.09	10.17	9.49–10.83
v_{mp} (m/s)	6.08	3.44–7.21	3.19	2.69–3.29	9.02	8.61–9.32
v_{me} (m/s)	9.76	6.54–12.01	7.82	5.71–9.04	15.15	13.84–16.52
c (m/s)	7.60	4.72–9.19	5.10	3.94–5.64	11.65	10.94–12.26
k	2.41	2.07–2.51	1.78	1.67–1.92	2.26	2.14–2.37
ρ (kg/m ³)	1.235	1.224–1.246	0.991	0.982–1.001	1.235	1.233–1.240
P (W/m ²)	344.3	102.9–558.1	177.9	80.7–243.1	1103.5	871.1–1384.3
WT design parameters						
H_{hub} (m)		10–160		10–160		50–150
P_r (kW)	1479	1–3400	1512	1.5–3500	3731	2000–8000
D (m)	76	3–131	80	3.2–131	109	80–164
$\Phi = v_r/v_i$	4.328	2.250–7.500	4.368	2.250–7.500	3.914	3.500–5.000
$\eta_r = P_r / [(1/2)\rho A v_r^3]$	0.251	0.101–0.412	0.232	0.101–0.395	0.251	0.159–0.367
Paired parameters						
$\beta = v_m/v_i$	2.537	1.103–4.054	1.723	1.008–2.654	2.986	2.427–4.250
v_r/c	1.701	1.193–2.608	2.345	1.656–3.313	1.205	0.997–1.497
$\eta_T = AEY/E_a$	0.251	0.160–0.371	0.185	0.114–0.230	0.183	0.145–0.219
Energy output and cost parameters						
A_{WT} (%)	99.38	98.60–99.90	99.36	98.60–99.90	98.82	98.60–99.90
CF (%)	35.52	13.34–53.67	14.59	5.00–20.94	51.83	44.60–57.80
$LCoE$ (\$/MWh)	232	58–4869	514	163–7995	109	95–158

^a Vertical profiles are based on 26,280 1-h records over the period 01/01/2013–31/12/2015.^b No. processed WTs: 377 (Cabauw and Boulder); 23 (FINO3).^c Values of WT design, paired, energy output and cost parameters refer to energy yield computations performed for the two z -varying lists of candidate WTs retrieving minLCoE and maxCF.

Table 5

WTs performing the optimal site matching by optimization condition at the three selected sites (2013–2015)^{a,b}.

Site	Optimization		WT model	H_{hub} (m)	P_r (kW)	D (m)	v_i (m/s)	v_r (m/s)
	condition	score						
Cabauw								
	MinLCoE	58 \$/MWh	VENSYS 82-1500	100	1500	82.3	3.0	12
	MaxCF	53.67%	W2E HARVESTER 2.0	140	2000	116	3.5	10
Boulder								
	MinLCoE	163 \$/MWh	LEITWIND LTW77-800	80	800	76.7	3.0	11
	MaxCF	20.94%	W2E HARVESTER 2.0	140	2000	116	3.5	10
FINO3								
	MinLCoE	95 \$/MWh	NORDEX N90-2500	80	2500	90	3.5	14
	MaxCF	57.80%	SIEMENS SWT-2.3-101	100	2300	101	3.5	12

^a Vertical profiles are based on 26,280 1-h records over the period 01/01/2013–31/12/2015.

^b No. processed WTs: 377 (Cabauw and Boulder); 23 (FINO3).

5.2 Cabauw

According to the European wind resource atlas [59] over “open plain” sites, Cabauw can be classified as a medium site, as at 50 m v_m is equal to 6.1 m/s and P to 242 W/m². Since relying on a 213-m tall met mast with densely installed sensors up to 200 m (Table 2), profiles at intermediate heights are well approximated all over the 10–160 m height range; valid data percentage is also remarkable (98.08%). With annual average α values ranging 0.203–0.267, the site exhibits a significantly pronounced vertical profile of both v_m and particularly P (Fig. 4a). Interestingly, k vertical profile increases from 2.07 (10 m) to a maximum of 2.51 (50–70 m), and then decreases above to 2.32: this Cabauw k profile is similar to the one found by Justus et al. [31] at four tower sites in US, increasing with height up to a maximum at 60–70 m; conversely, this k outcome contrasts with Chang et al. [2], who stated that “the shape parameter is independent of WT hub height”. As a result, the shape of wind speed Weibull distribution at Cabauw exhibits a substantial height variation (Fig. 3a).

Pairing all available onshore WT's to the Cabauw's wind resource characteristics across the full 10–160 m height range resulted in the statistics summarized in Table 4, where for overall WT energy losses a 10.07–12.33% range was considered (Table 3). A very wide range of WT design parameters (e.g. P_r of 1–3400 kW, and D of 3–131 m), and resulting performance parameters (e.g. CF of 13.34–53.67%, and $LCoE$ of 58–4869 \$/MWh) was observed in selecting WT's satisfying both optimization criteria. Height variations of minLCoE and maxCF are quite different (Fig. 4b): while maxCF quite regularly increases according to an exponential-like shape, minLCoE decreases dramatically up to about 25 m, smoother up to 70–80 m, then basically remains unchanged at heights above. The irregular pattern exhibited by these vertical profiles is due to the nonhomogeneous distribution of available WT's characteristics (Fig. 1), as also shown by Carrillo et al. [9]: both objective functions are thus not continuous and derivable functions.

In Table 5 details of WT optimal site matching, sorted by optimization condition, are shown. The minLCoE condition (58 \$/MWh) is satisfied by using the 1500-kW VENSYS 82 WT with H_{hub} =100 m, while the maxCF condition (53.67%) is achieved by using the 2000-kW W2E HARVESTER with H_{hub} =140 m. This highlights that the search for WT site optimization is primarily a search for the optimum H_{hub} . Furthermore, minLCoE is not achieved by indefinitely increasing H_{hub} , but rather through detection of an “optimum” H_{hub} obtained as a unique solution of the optimization procedure. This outcome is consistent with findings by Ashuri et al. [20]: since WT tower has the highest cost trend exponent, the extra energy captured by larger WT's (upscaling) does not compensate for the higher $C_{initial}$, and thus $LCoE$. The power curves of optimal WT's and corresponding wind speed Weibull distributions are shown in Fig. 3a.

Within a survey worldwide updated to the year 2014, IEA-ETSAP and IRENA [43] reported typical values of $LCoE$ ranging 60–120 \$/MWh for onshore and 100–210 \$/MWh for offshore projects. Therefore, with $LCoE$ =58 \$/MWh Cabauw is definitely a potential site for an economic viable wind energy project. As a comparison, this Cabauw optimization returned an $LCoE$ slightly higher than those obtained by Mirghaed and Roshandel [19] (46.6–54.5 \$/MWh) using 1030–1105

473 kW WTs at three onshore sites in Iran, which at 40 m AGL were affected, however, by v_m values
474 (8.91–10.5 m/s) remarkably higher than the one at Cabauw (5.74 m/s).

Fig. 4. Annual average vertical profiles (10–160 m) observed 2013–2015 at Cabauw of: (a) site's characteristics (v_m , k and P); (b) minLCoE and maxCF using 377 WTs. Dashed lines denote H_{hub} of the two WTs (see Table 5) achieving minLCoE (red) and maxCF (green) over the full height range.

5.3 Boulder

With 50-m v_m of 4.5 m/s and P of 153 W/m², Boulder would be classified as a “poor” (or “class 1”) site based on the NREL wind power classification (http://www.nrel.gov/gis/wind_detail.html).

Though the valid data percentage is remarkable (98.95%), vertical profiles above 80 m are affected by a certain degree of approximation (Table 2). Compared to Cabauw, Boulder exhibits lower annual average α values, steadily decreasing with height (0.133 to 0.100), which result in smoother vertical profiles of both v_m and P (Fig. 5a). Also, different from Cabauw, the k vertical profile steadily decreases with height (1.92 to 1.67). In applying all available onshore WTs to Boulder (Table 4) an 11.93–14.14% range of overall WT energy losses was accounted (Table 3). A wide range of WT design, energy output and cost parameters was again observed in seeking WTs achieving minLCoE and maxCF per height.

Vertical profiles of minLCoE and maxCF are quite similar to those at Cabauw (Fig. 5b). However, a closer analysis reveals that the overall minLCoE vertical gradient is lower, and that in minLCoE pattern there is no transition between a dramatic (up to 60 m) and basically negligible decrease at heights above. Furthermore, from a certain height (about 45–50 m) upwards minLCoE and maxCF exhibit an almost mirrored contrasting pattern ($r=-0.797$). Interestingly, as for the maxCF condition, Boulder is best suited by using the same WT and same H_{hub} as at Cabauw (Table 5), while the minLCoE condition is met by using the 800-kW LEITWIND LTW77 WT with $H_{hub}=80$ m; however, far higher minLCoE (163 \$/MWh) and lower maxCF (20.94%) are achieved herein. It should be noted that, as at Cabauw, the minLCoE condition is met at Boulder at lower heights than the maxCF condition. The outcome from both these onshore locations is consistent with findings by Mirghaed and Roshandel [19] that, for each site, a specific optimal configuration and size would minimize $LCoE$.

On the other hand, based on the typical $LCoE$ values reported above for onshore sites (60–120 \$/MWh), with $LCoE=163$ \$/MWh Boulder is a site where the installation of a wind farm in the area would not be economically viable.

Fig. 5. Same as Fig. 4, but at Boulder.

509 5.4 FINO3

510 Since affected by 50-m v_m equal to 9.7 m/s and P to 871 W/m², FINO3 can be defined as a
511 “superb” (maximum class) “open-sea” site [59].

512 The valid data percentage (82.49%) is lower than onshore (Table 2); also, vertical profiles above
513 95–100 m are affected by a certain approximation. FINO3 annual average α values are lower than
514 onshore, generally increasing with height (0.041 to 0.110), barring 60–70 m. P and particularly v_m
515 vary very slightly with height: the small overall excursions of v_m (13%) and ρ (0.6%) result in a
516 similarly quite smooth P vertical profile (Fig. 6a). As at Boulder, the k vertical profile decreases
517 with height (2.37 to 2.14). Also, at FINO3 wind speed Weibull distributions do not appreciably vary
518 with height (Fig. 3c).

519 With respect to the onshore sites, owing to the far smaller number of available WTs with not
520 particularly uniformly distributed WT characteristics (Fig. 1), along with not particularly wide P
521 vertical variation (Fig. 6a), WT application to FINO3 across the full 50–150 m height range
522 returned substantially different statistics (Table 4). The preliminary search for WTs achieving
523 minLCoE and maxCF at any given height, accounting for a 10.98–13.22% overall energy losses
524 (Table 3), was performed by employing design parameters of P_r ranging 2000–8000 kW, and D
525 ranging 80–164 m. Unlike at both onshore locations, at FINO3 the overall range of both CF (44.60–
526 57.80%) and $LCoE$ (95–158 \$/MWh) is very narrow (Table 4). Furthermore, vertical profiles of
527 minLCoE and maxCF are neither contrasting nor almost-mirrored as at the onshore sites: CF
528 weakly increases exhibiting a “paunchy” pattern 75–130 m, while $LCoE$ decreases slightly up to 85
529 m, and then increases slightly at higher heights (Fig. 6b).

530 Also at the offshore location the two performance conditions are satisfied by using different WTs
531 and different H_{hub} values: minLCoE (95 \$/MWh) is achieved by using the 2500-kW NORDEX N90
532 WT with H_{hub} =80 m, while maxCF (57.80%) by using the 2300-kW SIEMENS SWT-101 WT with
533 H_{hub} =100 m. Furthermore, as at both onshore locations, also at FINO3 the minLCoE condition is
534 met at lower heights than the maxCF condition.

535 In any case, at FINO3 there is no need to go too high with wind energy capture, as even at the
536 lowest H_{hub} of available offshore WTs (50–60 m, Fig. 1a) the site proves to offer prospects for
537 profitable energy projects.

538 Summarizing, based on the typical $LCoE$ range reported above for offshore sites (100–210
539 \$/MWh), with $LCoE=95$ \$/MWh a wind farm project at FINO3 might be economically attractive.
540 However, because of the higher uncertainty affecting the $C_{initial}$ computation through Eq. (23) at
541 offshore locations, this $LCoE$ should actually be taken as a mere indicative amount, particularly
542 while considering the site is located 80 km off the coast, and therefore the costs for the balance of
543 system would likely be higher than the currently considered 52% rough estimate.

544

Fig. 6. Same as Fig. 4, but at FINO3, with vertical profiles between 50 and 150 m, and using 23 WT.

6. Improving site optimization through the SOMs

6.1 SOM settings

The SOM algorithm was applied to the annual average vertical profiles of the following variables: k , P , P_r , D , Φ , η_r , η_T , β , v_r/c , A_{WT} , CF , and $LCoE$. This dataset includes those values, varying by z steps, obtained during phases (ii) and (iii) of the optimization procedure (§ 5.1). The SOMs for each location were visualized by component planes represented by the above-selected variables. To avoid redundancy, those variables with vertical patterns strictly correlated to each other were withdrawn, such as v_m and H_{hub} , both strongly correlated to P : v_m by $r=0.982$ – 0.995 , and H_{hub} by $r=0.981$ – 0.999 . Therefore, the SOM component plane of P should be considered the same as v_m and H_{hub} .

SOM training, conducted according to the Kohonen's algorithm [47], was performed using 20,000 iterations (more than 500 times the number of lattice neurons), and initial values of 0.9 (close to 1) for the learning rate and 5 units (more than half the lattice's diameter) for the neighbourhood radius. The Mexican hat neighbourhood function, proposed by Kohonen [49], was employed as returning a wider (more reliable) variables' variation range than the most commonly used Gaussian function. For evaluating the goodness of SOM, the error measure proposed by Kaski and Lagus [60], which combines quantization and topographic errors, was adopted.

The final SOM structure was established on two layers of neurons, i.e.: (i) an input layer, consisting of a number of neurons corresponding to the 2013–2015 annual average vertical profiles of the above-selected variables; (ii) an output layer, consisting of 36 neurons, visualized by hexagons, organized in two-dimensional grids with 6 rows and 6 columns. Thus, the number of trained neurons in the output layer (36) accounted for 2% of the neurons of the input layer (1800). All SOM computations were performed using Living for SOM (v. 1.4.4), an open-source tool freely available at: <http://livingforsom.com>.

The results of the SOM application are presented in Fig. 7 (Cabauw), Fig. 8 (Boulder), and Fig. 9 (FINO3). For an easier SOM analysis, a key is provided in these figures: both hexagons corresponding to minLCoE and maxCF neurons are highlighted, as well as their related values and distribution percentile ranks for each component plane are shown.

6.2 Cabauw

At Cabauw (Fig. 7), the neuron corresponding to the minLCoE condition (72 \$/MWh) matches with the one corresponding to the maxCF condition (37.71%). Therefore, contrary to the previous vertical profile analysis (§ 5.2), the SOMs are capable of recognising that these two optimization conditions are not apart, but belong to the same neuron, thus suggesting that one choice is equivalent to the other: this implies that selecting the WT with the lower H_{hub} , out of the two detected in Table 5, is likely the most economically viable solution. This minLCoE=maxCF neuron (hexagons highlighted in light blue, with an occurrence of 17.2%) is associated to maxima of site's characteristics (P), WT design parameters (P_r , D , Φ and η_r), paired parameters (β), as well as to minima of a paired parameter as v_r/c . Conversely, the role of η_T , associated by the 20th percentile of its distribution, is secondary: as also observed by Chang et al. [10] at four onshore coastal locations in Taiwan, η_T cannot be taken as a reliable energy yield indicator.

A closer SOM analysis, focused on the whole lattice topology of each component plane rather than single neurons, reveals that the topology patterns of CF and $LCoE$ are almost perfectly mirrored, thus suggesting that at Cabauw pursuing either minLCoE or maxCF over their entire dataset leads to the same result. Furthermore, the CF topology exhibits the same min-to-max orientation (BL-to-TL) as P , P_r and D , which confirms that increasing WT design parameters such as P_r and D results in a general CF increase (and thus $LCoE$ decrease). A similar SOM topology is exhibited by β (min-to-max) and v_r/c (max-to-min). Compared to CF and $LCoE$, SOM topology for η_T and A_{WT} is different, as their min-to-max (η_T) and max-to-min (A_{WT}) orientation, which is quite mirrored, is BL-to-TR. Also SOM topology for k differs from both CF and $LCoE$. Therefore, since

poorly associated to k , at Cabauw CF is quite insensitive to the shape of wind speed Weibull distribution (Fig. 3a): this score is consistent with the CF - k curves by β and Φ plotted by Pallabazzer [6], indicating that the effect of k on CF can be neglected for currently achieved values of β and Φ .

603

6.3 Boulder

Similarly to Cabauw, at Boulder (Fig. 8) the two conditions of minLCoE (207 \$/MWh) and maxCF (12.66%) match. This minLCoE=maxCF common neuron (hexagons highlighted in light blue, with an occurrence of 17.4%) is associated to maxima of P , P_r , D , Φ , and β , and to minima of k and v_r/c ; in addition to the Cabauw SOM scenario, this neuron is also associated to the highest η_T .

However, the SOM analysis performed by considering the whole lattice topology reveals that, unlike at Cabauw, at Boulder the patterns of CF and $LCoE$ are not mirrored, as min-to-max CF orientation is TL-to-BR, while $LCoE$ does not exhibit a monotonic pattern since affected by two local minima. Actually, $LCoE$ topology pattern is quite similar to P , P_r , D , and η_T ; conversely, min-to-max CF orientation is quite similar to orientations of β (min-to-max) and v_r/c (max-to-min). This outcome suggests that a different parameters setting may either result in an $LCoE$ reduction or CF increase, but not both conditions at the same time: in terms of WT design parameters, for example, increasing P_r and D implies a direct $LCoE$ reduction. Furthermore, confirming findings by Pallabazzer [6], increasing β results in a CF increase; as at Cabauw, SOM topology pattern of CF is also significantly anti-correlated to v_r/c ($r=-0.733$).

Summarizing, outcomes from Boulder are consistent with those returned by Fuglsang et al. [5], who suggested that increasing D and H_{hub} increases annual energy yield. However, as noted by Maki et al. [18] and Ashuri et al. [20], at some point the increase in annual energy yield is not sufficient to outweigh the increase in $LCoE$, such as optimum values of both H_{hub} and D shall be detected which correspond to local minima for $LCoE$.

624

625 6.4 FINO3

626 A substantially different SOM scenario than at the onshore sites can be observed at FINO3 (Fig.
627 9), where minLCoE neuron (102.3 \$/MWh, with an occurrence of 6.7%), is associated to the 45th
628 percentile of the *CF* distribution, while maxCF neuron (52.97%, 12.8% of events) is associated to
629 maximux *LCoE* neuron. However, as described in § 5.4, this SOM scenario is likely due to the very
630 narrow range of both *LCoE* and *CF* component planes, which results from the small number of
631 processed WTs as well as a fairly slim *P* vertical variation.

632 At FINO3, *CF* topology exhibits a clear similarity with *P*, *P_r*, and *D*, as well as (mirrored) with
633 η_T , and v_r/c , thus suggesting that maxCF should be pursued by increasing WT size, or by decreasing
634 η_T or v_r/c . Conversely, *LCoE* topology is quite similar (though with the same orientation) with *P_r*
635 and *D*, and to a lesser extent with *P* (and thus H_{hub}), meaning that H_{hub} plays a minor role herein:
636 since FINO3 is a strongly energetic site even at the lowest H_{hub} of available offshore WTs (50–60
637 m), these results confirm that to minimize *LCoE* it is pointless going too high with wind resource
638 capture. Furthermore, although not exactly similar to *LCoE* max-to-min orientation, A_{WT} min-to-
639 max orientation suggests that availability is a key factor to minimize *LCoE* at FINO3. With a SOM
640 topology mirrored vs. *CF* and significantly dissimilar vs. *LCoE*, at FINO3 *k* pattern is even more
641 different from *CF* and *LCoE* than onshore, thus indicating that its role is minor.

642 In any case, since *LCoE* max-to-min orientation (TR-to-BR) is clearly different from *CF* min-to-
643 max orientation (BL-to-TR), SOM analysis at the offshore site reveals, even more dramatically than
644 at Boulder, that the two optimization conditions are not necessarily associated, and thus that they
645 cannot be concurrently satisfied: at FINO3 *LCoE* cannot be minimized by increasing WT design
646 parameters such as *P_r* or *D*. This outcome contrasts with both offshore findings by Snel [45] that a
647 larger diameter with more annual energy yield becomes economically attractive, and by Fuglsang et
648 al. [5] that *LCoE* may be primarily reduced through increased annual energy yield from increasing
649 WT diameter.

Cabauw

Fig. 7. SOM component planes obtained at Cabauw from 2013–2015 annual average vertical profiles (10–160 m) for the following parameters: site (k and P); WT design (P_r , D , Φ and η_r); paired (η_T , β and v_r/c); energy output (A_{WT} and CF); cost ($LCoE$). A total of 377 WTs were processed. The 12 panels are linked by position so as the hexagons in a certain position correspond to the same map unit. Hexagons highlighted in light blue correspond to the minLCoE neuron (in this case, matching with the maxCF neuron): for each component plane, numerical values (and distribution percentile ranks in brackets) of this minLCoE=maxCF neuron are also reported.

Boulder

Fig. 8. Same as Fig. 7, but at Boulder. Neurons of minLCoE and maxCF are again matching.

FINO3

Fig. 9. Same as Fig. 7, but at FINO3, with vertical profiles between 50 and 150 m, and processing a total of 23 WTs. Neurons of minLCoE and maxCF are not matching: hexagons highlighted in light blue correspond to the minLCoE neuron, while those highlighted in grey correspond to the maxCF neuron.

7. Conclusions

A WT optimal site matching procedure was developed and applied on two different onshore and one offshore sites, each with a tall met mast installed: (i) Cabauw, a flat and sea-level inland site with medium energy potential; (ii) Boulder, an elevated mountain site with fairly complex terrain and “poor” potential; (iii) FINO3, an offshore platform 80 km off the coast with “superb” potential. These sites are real case studies approximately belonging to exemplary wind climates as defined in the literature. Sites' characteristics were thoroughly assessed by constructing wind resource vertical profiles based on three years (2013–2015) of 1-h observations collected at mast sensor heights: for each hour, at heights where sensor information was not available variables were vertically interpolated/extrapolated by a step of 2 m. A database of 377 onshore and 23 offshore commercial WTs was used: WT power curves were not fitted, but rather explicitly treated. Two objective functions have been considered: minimizing *LCoE* and maximizing *CF*.

In addition to detecting the most suitable WT for each site, SOMs were used to provide further insight into those parameters mostly influencing site optimization. A number of approximations have been introduced, as detailed in the following. Only single WTs have been considered, thus neglecting any WT array wake interferences. WT optimization has been pursued by disregarding all site's turbulence issues and WT turbulence regulation compliances. In the *LCoE* computation, initial capital cost and annual costs have been assessed through a simplified approach based on average statistical values referring to the current US market: this resulted in a higher uncertainty in calculating initial capital cost for the offshore site. A parametric approach was adopted in assessing WT capital cost as an increasing function of P_r , D and H_{hub} . For heights above the highest available sensors, v and T profiles have been extrapolated through extension of lower-range profiles. A maximum tolerance (± 2 m onshore and ± 5 m offshore) was taken between H_{hub} and estimates/observations height.

693 As a result, maximizing capacity factor was confirmed to be a *good* objective function, though
694 not the *best*, which was minimizing *LCoE*. This study proved that the exact matching of these two
695 optimization conditions (such as at Cabauw) is actually a special case, as in general they do not
696 necessarily match: variously setting WT design and paired parameters may either result in an *LCoE*
697 reduction or capacity factor increase, but both of these conditions do not occur concurrently.

698 A number of lessons have been learnt from this study in relation to increasing *CF* and/or
699 decreasing *LCoE*.

700 Onshore:

- 701 • higher site's energetic potential (P) is of course beneficial, but its pattern is closer associated to
702 *LCoE* than *CF*;
- 703 • minimum *LCoE* is achieved at lower heights than maximum *CF*;
- 704 • at the two sites, maximum *CF* is achieved by using the same WT and same H_{hub} , while for
705 minimizing *LCoE* two different WTs with different H_{hub} values were necessary;
- 706 • WT availability is not particularly decisive on both *CF* and *LCoE*;
- 707 • the effect of k is somewhat unclear on both *LCoE* and *CF*;
- 708 • among WT design parameters, P_r , D , and Φ mostly affect *LCoE*;
- 709 • as for paired parameters, η_T generally impacts on *LCoE*, while β and v_r/c on *CF*.

710 Offshore:

- 711 • the two optimization conditions are clearly not associated;
- 712 • the same WT design parameters as onshore (P_r and D) are the most effective on *LCoE*, though
713 they should be minimized to minimize *LCoE*;
- 714 • P (and thus H_{hub}) are not decisive parameters in minimizing *LCoE*: since FINO3 is a strongly
715 energetic site even at the lowest H_{hub} of available offshore WTs (50–60 m), to minimize *LCoE* it
716 is pointless going too high with energy capture;
- 717 • as onshore, minimum *LCoE* is achieved at lower heights than maximum *CF*;
- 718 • more apparently than onshore, WT availability is a key factor for minimizing *LCoE*;

- the role of k to both $LCoE$ and CF is even less decisive than onshore, as confirmed by the quite height-insensitive wind speed Weibull distributions;
- the same paired parameter as onshore (v_r/c) mostly affects CF : increasing v_r/c leads to CF increasing.

Summarizing, this study pointed out that the search for WT site optimization is primarily a search for optimum H_{hub} . One of its key findings is that minimum energy cost may not be achieved by indefinitely increasing H_{hub} , but rather through detection of an optimum value obtained as a unique solution of the optimization procedure: since the WT tower has the highest cost trend exponent, the extra energy captured by larger WTs (upscaling) does not compensate for the higher initial capital cost, and thus $LCoE$. This study also demonstrated that the SOM unsupervised learning ANN-based model greatly improves the “traditional” analysis focussed on the mere variable vertical profiling. SOM capability of recognising the cluster structure of all parameters influencing WT site optimization shed further light on their mutual relationship, thus proving to be an ideal tool to address the non-convex nature of this crucial issue.

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