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A review and recent developments in the optimal wind-turbine micro-siting problem

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ABSTRACT

This paper presents a review of the current state of the art solutions to the problem of wind farm optimal design. The aim of this work is to present the problem by identifying the most relevant issues involved in the design of a wind farm, as well as to discuss the optimization techniques and wind farm models used in the published literature.

An appropriate wind turbine layout is vital in order to obtain adequate performance in relation to the exploitation and operation of the plant during its lifespan. There are several factors that influence wind farm design, chief among them are the calculation of the overall energy yield by the wind farm and the initial investment. The energy produced depends on the local wind conditions and the interference caused by wind turbines nearby. The investment is mainly related to wind turbine acquisition, civil works and electrical infrastructure. However, these are not the only items that influence the design of a wind farm since economic indicators, environmental issues, local regulations, or the presence of wind farms should also be taken into account when deciding the design of the wind farm.

Even in the case of the most simplified objective function (maximizing the annual energy produced) the optimization problem cannot be solved by classical optimization techniques. To cope with this problem, most authors have used meta-heuristics techniques which have proved to be efficient when searching for the optimal solution to this problem.

The purpose of this paper is to review previous work by offering a clear outline of the latest advances, as well as to highlight the main aspects which need to be taken into account when tackling the wind farm design problem. In addition, in a conclusion of the review, future needs have been identified.

Contents

Abbreviations: ACO, ant colony algorithm; AEP, annual energy produced; CFD, computational fluid dynamics; CMA-ES, covariance matrix adaptation evolution strategy; GPSO, Gaussian particle swarm optimization; GA, genetic algorithm; HV, high voltage; LCOE, levelized cost of energy; *LPC*, levelized production cost; MV, medium voltage; *NPV*, net present value; PSO, particle swarm optimization; SPEA, strong Pareto evolutionary algorithm; WF, wind farm; WT, wind turbine.

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1. Introduction

This paper reviews the optimal wind turbine micro-siting problem, offering a survey of the relevant technical literature published on the latest developments on this issue.

Although most existing research focuses on the optimization of onshore wind farms, the optimization techniques and the process of assessing the annual energy produced by the wind farm can be applied to offshore plants with minor variations. The main difference is in the model used for calculation of the initial investment, which must be tailored for the case of offshore wind farms (OWFs).

The first step to be taken when planning a wind farm (WF) is the site selection whereby several factors must be taken into account, which include: the wind resource, land availability, environmental conditions, possibility of connection to the electrical transmission system, and proximity to access roads. This issue has been addressed and solutions have been offered in several papers [1–4] which enable the conditions necessary for the implementation of a wind project on a particular plot of land to be established.

After selecting the plot, the next step consists of solving the problem studied in this work, i.e., the optimal selection of the geographical location of each individual wind turbine (WT). Although there are currently several examples of commercial software available that enables the design of a WF to be undertaken, the problem is usually tackled by experts or consultants by following a set of guidelines, which ensures a minimum level of production. The general trend (in the case of onshore WFs) has been to iteratively place the WTs in positions where the wind potential is the greatest, whilst observing a given distance between WTs in the prevailing wind direction in order to prevent any excessive wake effect (when a wind turbine captures part of the kinetic energy of the wind that goes through its rotor, it extracts a certain amount of it from the wind flow, generating a wake of wind that is slower and more turbulent in the rear area). In offshore WFs, the general trend has been to place the WTs in regular structures, whilst maintaining a greater distance between those WTs affected by the prevailing wind direction.

However, several studies show that such configurations are not necessarily optimal in terms of total energy and final profitability of the project [5–12]. This lack of optimality is mainly due to the wake effect, since in a wind farm composed of a cluster of turbines, this disturbance causes the wind speed field to be highly dependent on the position of each individual WT. This can be observed in Fig. 1, where the following arrangements of the Middelgrunden offshore wind farm [7] are shown: (a) the actual layout of the wind turbines; (b) a symmetrical optimized layout, and (c) an irregular optimized layout. According to [7], the layouts shown in (b) and (c) would provide an increase in the annual energy produced (AEP) of 5% and 6%, respectively. Obviously, this improvement in AEP would have significant consequences in terms of annual revenue and hence on the profitability of the project. The attention paid to optimization techniques applied to the problem of the micro-positioning of WTs on a wind farm is therefore justified.

The AEP is not the only factor to take into account when undertaking the design of a WF, since it is also necessary to consider other factors, such as the initial investment of the project, (which depends, for an onshore WF, on aspects such as acquisition of WTs, electrical infrastructure, access roads, and foundations, among others), and issues that influence the annual cash flow, such as maintenance and operation costs, and electrical losses. Furthermore, in order to financially evaluate the project, it is necessary to ascertain several economic variables, such as the sale price of energy and the evolution of the interest rate. In Fig. 2, an overview is presented of those diverse factors and relationships that must be borne in mind when undertaking the design of a WF. All these factors lead to the involvement of extremely complex mathematics in the solution for the optimal micro-siting of WTs.

Furthermore, the design of WFs is not only subject to internal factors but it can also depend on the design of other nearby WFs. When designing a wind power plant, conflicting situations involving other nearby projects have to be taken into account. These conflicting

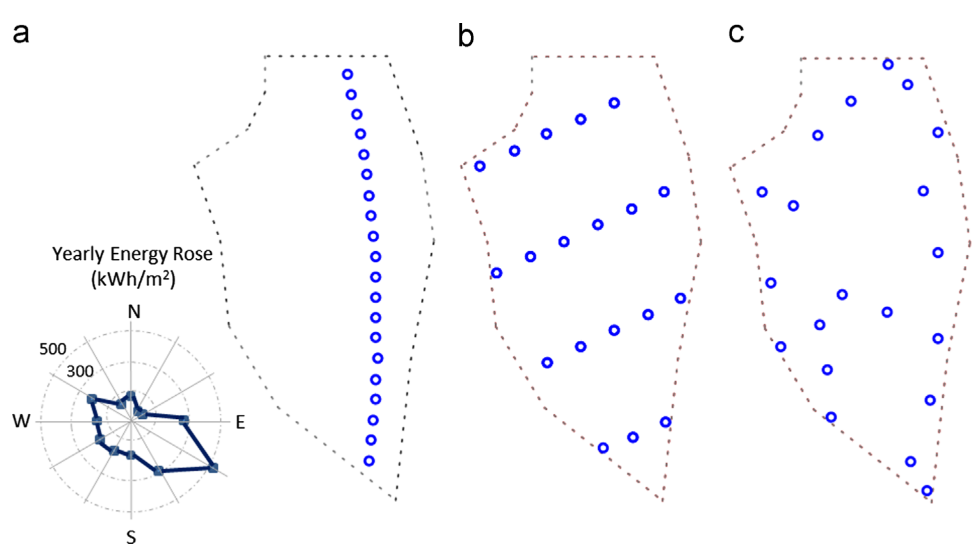

Fig. 1. Layout of the Middelgrunden offshore wind farm: (a) actual, (b) optimized with symmetrical constraints, (c) optimized [7].

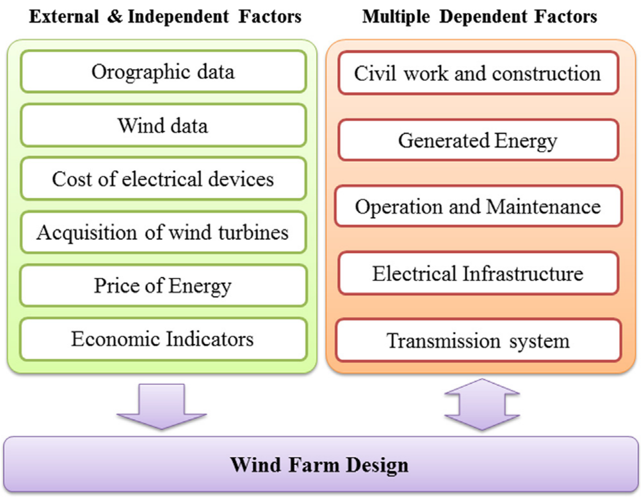

Fig. 2. Relationships between the various modules/factors of the optimization problem.

situations can arise when there are other nearby wind farms close to the location of the project under study. The wake effect produced by other nearby wind farms can affect the AEP produced and hence the economic profitability of the project. When nearby WFs already exist, the perturbation of the airflow can be easily studied by analysing the wake effect introduced by other wind farms. The problem is different when nearby wind farms are planned to be constructed but they do not already exist, in this situation decision making using game theory can provide a suitable solution that minimizes the risk associated with the decisions made by the developers of other wind farms [8]. This circumstance can be highly significant in the case of offshore wind farms where most countries have established delimited zones where OWFs can be installed. Usually the distance between these zones is not enough to completely avoid the wake effect produced by other wind farms. This fact, together with the usual high compactness degree (number of WTs per area) of offshore wind farms, leads to considerable wake effect losses that can reach approximate values 10–15% [9].

A different conflicting situation can arise when a wind farm is built with a relatively low compactness degree (this situation can be due to limited financial resources of developers, regulation or market limitations, etc.). In this case, if the developer does not own the terrain, there is a possibility that later on other investors will choose to use the same plot of land and could install wind turbines even in the middle of the previously existing wind farm thus seriously affecting the expected AEP and reliability of components due to the increased turbulence. Without going into the question of the legal right of access to the wind resource which is out of the scope of this paper [13], decision making using game theory can be used in this case to minimize the impact of installing new WTs in the same plot or even to design the WF so that the location of new WTs would not be profitable.

A similar problem, but different since it does not involve decision making under conflict, would be the construction of the wind farm in several stages in order to properly design the wind turbine layout at each stage to maximize the AEP while minimizing the initial investment. Real options theory seems to be a suitable tool to tackle this problem [10].

Table 1 shows the typical cost breakdown of a WF, compiled and adapted from [14–16]. As shown, most of the investment costs are related with the acquisition of WTs. The cost of foundations and electrical infrastructure also play an important role. However, the fraction corresponding to each of the factors can vary depending on the particular characteristics of the WF under study.

The analyzed problem has been solved by different approaches: from the simplest approaches whose aim is to maximize the AEP, to the most complex economic models which take into account the complete cost breakdown of the WF, in addition to several restrictions (forbidden zones, maximum investment and maximum number of WTs), and which also study the economic risk associated with uncertainty in the input data.

Table 1
Typical initial-cost breakdown of a WF.

	Onshore	Offshore
Wind turbines (%)	65–75	30–50
Electrical infrastructure (%)	1–10	15–30
Collector system	6–9	2–8
Transmission system	2–3	10–18
Substation	2–3	4–8
Civil work (%)	0–5	15–25
Installation and transport (%)	0–2	5–30
Other (%)	5	8
Overall cost (€/kW)	800–1100	1800–2650

The more complex the approach, the greater the amount of input data: for the maximization of energy it is necessary to ascertain the wind resource, the WT characteristics, and the dimensions of the plot. In the case of economic models of the WF that are more complete, it is also necessary to ascertain the costs of several factors, the evolution of economic indicators and, where relevant, the uncertainty about the input data.

It is worth noting that even for the simplest approaches, (the maximization of the AEP), the problem consists of both discrete and continuous variables, and is, therefore, an integer mixed-type problem. It exhibits manifold optimal solutions (convexity) and cannot be completely described in an analytical form. Therefore, the problem studied in this paper cannot be solved by classic optimization methods. Hence, most authors have solved the problem by meta-heuristic optimization techniques.

Another important factor to bear in mind is that the behaviour of meta-heuristic optimization techniques is affected by the size of the solution space. For the analyzed problem, the size of the solution space depends on the number of existing cells in the computational domain (the majority of the studies examined here have performed the optimization over a discretized plot of land) and the number of WTs. Moreover, according to the requirements of the problem, this number of WTs can also be a variable to optimize (thereby introducing additional complexity). In order to illustrate the dramatic increase of the solution space of the problem triggered by an increase in the WF size, the following example is proposed: assuming that the number of turbines to be installed at the WF, N_{WT}, is known and that the area under study has been divided into N_{cell}. The number of possible solutions can be calculated as the number of combinations of N_{cell} taking N_{WT} at a time without repetition, and is given by the expression:

$$N_{\mathrm{sol}} = \binom{N_{\mathrm{cell}}}{N_{\mathrm{WT}}} = \frac{N_{\mathrm{cell}}!}{N_t!(N_{\mathrm{cell}} - N_{\mathrm{WT}})!} \tag{1}$$

According to (1), it is possible to perceive the extraordinary increase in the complexity of the problem with each increment in the size of the WF. Therefore, as the size of the solution space increases, the parameters of the optimization algorithm should be appropriate for the complexity of the problem.

2. Literature review

In order to undertake the design of a wind farm, there are several issues to first consider. Most of these issues have been extensively studied in an individualized way, as a part of the complete

micro-siting problem: the study of wind behaviour [17–21], analysis of interactions between wind turbines (wake effect) [22–31], design of auxiliary facilities (access roads [32], electrical infrastructure [33–35], foundations [36–38]), reliability [39–42], economic issues [10–43], environmental assessment [44–46], to name but a few. The problem discussed in this paper covers all these factors, since the position of each of the WTs on a WF is subject to a greater or lesser extent to each of the factors mentioned above.

Currently, there are several commercial programs that enable the wind resource to be assessed at the placement. The most popular of these software packages is WAsP [47]. The main objective of this tool is to perform the wind resource assessment over the terrain under study by the taking into account the wind climate observation previously obtained at nearby meteorological station or at meteorological masts installed during the measurement campaign. WAsP estimates the wind resource at the placement by microscale flow analysis. However, the results obtained by this method have been proved not to be accurate enough when assessing complex terrain. Therefore, the last release of this software, WAsP 11, includes a module that allows assessing the wind behaviour in complex terrain using computational fluid dynamics (CFD). WAsP also offers other complementary tools/modules to help developers during the wind farm design such as evaluation of the energy yield of a wind farm taking into account the wake effect calculated using the Katic model [24], analysis of extreme wind speed conditions, wind shears and turbulence, etc.

A similar piece of software is WindSim [48] which assesses the wind resource in the placement under study using a CFD model based on a 3D Reynolds-averaged Navier–Stokes solver. The main objective of this tool is to pinpoint locations with better wind speed conditions and low turbulence in complex terrain so that designers can identify the most suitable positions for wind turbines during the wind farm design process.

In addition, Meteodyn [49] provides similar services by estimating the wind resource over the plot under study by means of CFD simulation. This software also allows integrating the results obtained with data provided by mesoscale analysis performed using other sources. Meteodyn also calculates the energy produced by a given WT's layout taking into account the Katic model [24] when evaluating the wake effect.

The main objective of all the above-mentioned software products is the assessment of wind resource which is vital information when undertaking a wind project. However, despite these tools enabling developers and designers to decide on wind farm design through assessing the annual energy produced by a wind farm for a given layout, the problem of optimizing the wind turbine layout is not the main aim of these tools. Nevertheless, there are other software packages which tackle the problem of optimizing WT layout.

Windfarmer [50] optimizes the layout of a wind farm for maximum return of investment. The computation of wake effects is performed by CFD based on a Reynolds-averaged Navier–Stokes solver. However, no in depth details of the optimization algorithm and the objective function used are provided. Additional features of Windfarmer enable the assessment of aspects such as uncertainty, noise, visual impact and electrical infrastructure among others.

WindPro [51] addresses the problem of optimizing the wind turbine layout by optimizing the annual energy produced by the wind farm. The wake effect is modelled using the Katic model [24]. This software optimizes the wind turbine layout according to whether or not the desired layout is random (the optimization method consists of sequentially adding WTs on the positions with maximum available energy), or symmetrical (WTs are located at fixed distances with the objective of optimizing the separation and angles among wind turbines). It is also worth mentioning the noise calculation module that allows assessing the noise impact and finding a suitable wind turbine layout which will meet noise requirements.

OpenWind [52] is an open source software that also tackles the optimization of the wind turbine layout of wind farms. The objective is to minimize the cost of energy production but no further details are provided about the optimization method used. Other modules include the calculation of deep array wake effect based on the modified Katic model [24], shadow flicker and uncertainty evaluation.

To date, several publications in relevant peer-reviewed scientific journals have appeared in which the optimization of a mathematical model of the wind farm has been addressed in order to undertake the optimal positioning of the WTs. The problem was presented by Mosetti et al. [53]. The objective was to maximize the AEP and to minimize the installation costs by assuming a rather simplified cost model of the wind farm (based on economies of scale and the overlapping of wakes). The optimization was performed by means of a genetic algorithm (GA) which selected the position of the WTs over a discretized plot of land. In 2001, Kiranoudis et al. [54] studied the optimization of the number of WTs on a WF by developing an analytical model of overall efficiency of the wind farm. Aytun Ozturk and Norman [55] used the cost model of the WF proposed by Mosetti et al., but in this study the objective function was slightly different. Although the authors initially proposed non-linear programming methods in order to optimize a set of simple cases, Aytun Ozturk and Norman [55] concluded that these methodologies are not applicable to the optimization of complex and more realistic cases, and hence in a second instance the authors proposed a heuristic optimization technique: a greedy algorithm.

A year later, Grady et al. [56] presented new work with the purpose of optimizing the layout of the WTs by means of a GA, but also included some improvements in the economic model regarding the work of Mosetti et al. Castro et al. [57] proposed the optimization through a GA that took into account a more complex and realistic cost model of the WF than that suggested in previous work. Marmidis et al. [58] addressed the same economic model proposed by Grady et al., but this time optimized by a Monte Carlo simulation. Elkinton et al. [59] proposed the levelized cost of energy (LCOE) for the case of offshore WFs. Şişbot et al. [60] suggested a multi-objective GA applied to a case study on the island of Gökçeada in Turkey which maximized the AEP and minimized the cost function proposed by Kiranoudis et al. [31]. Wan et al. [61] proposed an innovative approach which performed the optimization by means of a particle swarm optimization (PSO) algorithm. The main innovation included in that work was the consideration of a continuous computational domain rather than the discrete domain used in previous work. Mustakerov et al. [62] presented a study whose objective was the optimal selection of the WT model and diameter of the turbine based on a combinatorial approach that took into account the geographical distribution of WTs arranged in regular patterns. Kusiak and Song [63] proposed optimizing a multi-objective function by a strong Pareto evolutionary algorithm (SPEA) by considering a continuous computational domain, but in this case, over a circular plot of land. GAs are again addressed by Emami et al. [64]. In that paper, a new codification of the individual is proposed while the cost model of the wind farm remains the same as that implemented in [56]. Serrano et al. [65] retake the approach introduced by Castro et al. and include many aspects in the economic model such as forbidden zones, cost of foundations, and access roads. Serrano et al. [66] extended this work in 2011 by also including the optimal design of the electrical system of the WF through the study of its influence on the micro-siting problem of the WTs. Saavedra et al. [67] optimized a wind farm model, similar to that proposed by

Castro et al., by means of a GA and analyzed the influence of initial solutions obtained by a greedy algorithm on the final solution. Archer et al. [68] modelled a coefficient in order to consider the wake effect between wind turbines with the purpose of tackling the problem using Mixed Integer Linear Programming. Changsui et al. [69] optimized the objective function, given by Grady, by means of a fast greedy algorithm. In 2012 Ekonomou et al. [71] studied the selection of the optimum number of wind turbines by using artificial neural networks. Wan et al. [70] optimized the work proposed in [61], through a Gaussian particle swarm optimization (GPSO). Serrano et al. [72] studied the optimization of WFs included risk analysis techniques in order to take into account the uncertainty in wind resource. A similar approach was introduced by Messac et al. [73] who minimized the standard deviation of the unitary cost of energy by means of a PSO algorithm. Chowdhury et al. [74] optimized a new cost model of the wind farm based on the rotor diameter of the WTs by means a PSO algorithm. Eroğlu and Seçkiner [75] proposed an ant colony optimization (ACO) algorithm to optimize the same WF model as the proposed by Kusiak and Song [63]. Wagner et al. [76] maximized the AEP yield by the WF by means an effective local search algorithm. Rajper and Amin [77] proposed a GA in order to obtain the optimal number of WTs by minimizing the cost per unit power. Serrano et al. [78] also proposed an iterative method for the optimization of the layout of large offshore plants based on the rapid fading of the wake effect with increasing distance.

Additionally, there are other scientific papers, conference presentations, and technical reports that also address the optimization of the layout of wind turbines [79–130].

Among these, it is worth mentioning the work developed by Huang [79], [80] which introduced some enhancements the GA in order to improve the performance of the optimization algorithm. Wang et al. [81], [82] which analyzed the influence of the type of computational domain on the solution of the problem. In particular, the analysis focuses on the shape of the cell used for the discretization of the terrain. Wan et al. [83–85] optimized the problem by different techniques as a real-coded GA and a PSO algorithm. Chen et al. [86] included in the problem the possibility of selecting among several plots depending on the cost of land. Messac et al. [88–93] conducted several studies by analysing the influence of aspects as uncertainty, land configuration and terrain availability. Kwong et al. [96] studied the noise impact on the position of the turbines. Also Kwong et al. [97] conducted a similar study, but in this case took environmental impact into account. Castro et al. [111] proposed two nested GAs in order to optimize simultaneously the wind turbines layout and the electrical infrastructure. Salcedo et al. [115] made a previous review about the computational techniques applied to the WTs micro-siting problem. Finally, the optimization of a particularized model for offshore wind farms is proposed in [113, 114, 117, 123,124, 126–128,130].

3. Objective functions

This section describes the objective functions used in the analyzed works, starting with the simplest proposals, (which aim to maximize the AEP), to more complex models which take into account a complete economic model of the wind farm.

Maximization of the AEP of the wind farm is proposed by Kusiak et al. [60], and Wan et al. [74]. The annual energy generated, E_{WF}, is calculated taking into account the power curve of the jth WT, $P_{\mathrm{WT}\ j}(u)$, the actual wind speed while considering the wake effect, u', and the wind speed probability for the ith wind rose sector, $p_{ij}(u')$:

$$E_{\mathrm{WF}} = T \sum_{i=1}^{N_s} \sum_{j=1}^{N_{\mathrm{WT}}} p(S_{ij}) \int_{u_{ci\ j}}^{u_{co\ j}} P_{\mathrm{WT}\ j}(u'_{ij}) p_{ij}(u'_{ij}) du \tag{2}$$

where T is the number of hours per year (T=8760 h), $p(S_{ij})$ is the probability of occurrence for wind direction, i, at the position of the jth WT, N_s is the number of sectors into which the wind rose has been divided, and $u_{ci\ j}$ and $u_{co\ j}$ are the *cut-in speed* and *cut-out speed*, respectively.

Mosetti [53] proposed maximizing the AEP with the minimum cost of the wind farm by minimizing the following expression:

$$Obj = \frac{1}{E_{\mathrm{WF}}} \times w_1 + \frac{cost_{tot}}{E_{\mathrm{WF}}} \times w_2 \tag{3}$$

where w_1 and w_2 are the weights selected arbitrarily and $cost_{tot}$ the total cost of the WF:

$$cost_{tot} = N_{\mathrm{WT}} \times \left(\frac{2}{3} + \frac{1}{3} \times e^{-0.00174 \times N_{\mathrm{WT}}^2} \right) \tag{4}$$

Aytun Ozturk and Norman [55] studied the maximization of profit, calculated as:

$$Profit = \left[p_{\mathrm{kW\ h}} - \left(\frac{cost_{tot}}{E_{\mathrm{WF}}} \right) \right] \times E_{\mathrm{WF}} \tag{5}$$

where $p_{\mathrm{kW\ h}}$ is the selling price of energy and $cost_{tot}$ is the total cost of the WF proposed by Mosetti in (4).

The minimization of the ratio Cost/AEP is studied by [56,58,69], also using the cost model proposed in Eq. (4).

$$Obj = \frac{cost_{tot}}{E_{\mathrm{WF}}} \tag{6}$$

A new approach to the problem was introduced by Castro et al. [57] by maximizing the net present value (NPV) defined by expression (7).

$$NPV(x) = \frac{CF_1(x)}{1+r} + \frac{CF_2(x)}{(1+r)^2} + \cdots + \frac{CF_t(x)}{(1+r)^{LT}} - I_{\mathrm{WF}}(x) \tag{7}$$

where CF_i is the cash flow of each year, I_{WF} is the initial investment of the wind farm, x is the configuration of the wind farm, LT the lifetime of the project, and r is the discount rate of money. This approach enables a more complete and realistic model of economic behaviour of the wind farm to be considered. This work was extended by Serrano et al. [65] who introduced new economic aspects, such as the necessary investment in wind turbine foundations and access roads in the case of onshore wind farms. Serrano et al. [66] also entered the problem of electrical infrastructure optimum design through a secondary optimization algorithm. Saavedra et al. [67] optimized the layout of WTs by taking into account the NPV according to Eq. (7) and considering the costs of electrical connections between turbines and road construction.

A new approach was presented by Serrano et al. [72] who introduced probabilistic treatment of the problem using techniques of decision making in a risk environment. Two different objective functions were used depending on the decision criterion: maximum expected value or maximum expected utility, based on utility theory. With the first approach, the objective is to find the wind farm configuration with the maximum expected value of NPV:

$$EV_i = \sum_{j=1}^{m} NPV_{ij} \times p_j \tag{8}$$

where m is the number of scenarios, p_j is the probability of each scenario, and NPV_{ij} is the NPV of each considered layout and scenario.

The maximum expected utility criterion aims to maximize the expected utility:

$$EU_i = \sum_{j=1}^{m} u(NPV_{ij}) \times p_j \tag{9}$$

where $u(NPV)$ is the utility for a given value of the NPV calculated using the expression:

$$u(NPV(x)) = \begin{cases} \frac{1-e^{-(NPV(x)-NPV_{\min})/\rho}}{1-e^{-(NPV_{\max}-NPV_{\min})/\rho}} & \text{if } \rho \neq \infty \\ \frac{NPV(x)-NPV_{\min}}{NPV_{\max}-NPV_{\min}} & \text{if } \rho \to \infty \end{cases} \tag{10}$$

where ρ is the parameter of risk tolerance.

Messac et al. [73] also studied the uncertainty in the wind behaviour by minimizing the following objective function.

$$Obj = \frac{\sigma_{COE}}{COE} \tag{11}$$

where COE is the cost of energy, calculated by (12), and σ_{COE} is its standard deviation.

$$COE = \frac{Cost_{farm}}{E_{WF}} \tag{12}$$

The design of offshore wind farms has been studied by Lackner, [123] who took aspects into account, such as turbine cost, support cost structure and the electrical Interconnection cost, by minimizing the levelized production cost (LPC):

$$LPC = \frac{I_{WF}}{a_f E_{WF}} + \frac{C_{O\&M}}{E_{WF}} \tag{13}$$

where a_f is the annuity factor and $C_{O\&M}$ are the costs of operation and maintenance.

As can be seen, several objective functions have been used to optimize the wind turbine layout. Most of the studied works have analysed the simplified economic model introduced by Mosetti [53] which is in fact justified because the aim of these works was to show the ability of the proposed optimization methods. However, more complex and realistic models of the economic behaviour of the project have been introduced in other works in order to analyse the influence of aspects such as foundations, electrical infrastructure and uncertainty of input data, etc.

4. Energy production model

The evaluation of AEP is essential in order to analyze the micro-siting of WTs. In the works studied in this literature review, several statistical models of wind behaviour, the WT power curve and the wake effect have been proposed.

4.1. Behavioural model of the wind

The statistical behaviour of the wind is typically modelled by two different factors: wind direction and wind speed.

The wind direction is represented by the probability of occurrence for each of the sectors that make up the wind rose. A wind rose of thirty-six sectors is the most common discretization used [53,55,64,70]. Other studies have used wind roses divided into twenty-four [60], sixteen [64] and eight sectors [54,62,63]. Finally, [55] used a model of unidirectional wind.

The wind intensity model most widely used in the studies analyzed is a discretized distribution of wind speed made up of several averages for each of the wind directions [53,56,58,60,64,69,93]. However, the behaviour of the wind speed is typically characterized as a Weibull distribution [131,132]. The Weibull density function is defined by the parameters of scale, C, and shape, K, as shown in Eq. (14). The scale parameter, C, (usually take values between 5 and 12 m/s, depending on the location) is related to the average wind speed and shows how windy, on average, is the location. The shape parameter, K, (usually between 2.0 and 2.4) indicates how pointed the distribution is. This approach, adopted in [57,63,65–67,70], and [72], represents the evolution of wind speed over a long period of time, as shown in Fig. 3 by means of the cumulative probability versus the discrete distribution represented by the average speeds.

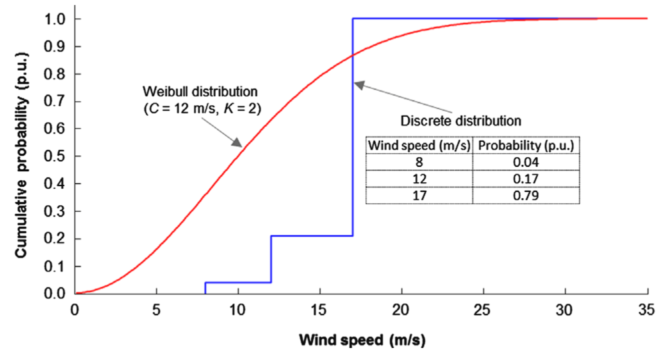

Fig. 3. Cumulative probability depending on wind-speed behavioural model assumed in the studies analyzed.

$$p(v) = \frac{K}{C} \times \left(\frac{v}{C}\right)^{K-1} \times e^{-\left(\frac{v}{C}\right)^K} \tag{14}$$

As can be seen from the results shown in Fig. 3, wind behaviour differs considerably depending on the approach. As previously stated, it is widely accepted that wind behaviour can be properly characterized by the Weibull distribution. Nevertheless, the use of discrete distributions can be justified in those studies where the aim is to show the ability of an optimization method rather than to analyse the wind farm layout using a more realistic objective function. The main advantage of using a discrete distribution is that the objective function can be evaluated using a relatively low computational cost, since the AEP is assessed by considering a few values of wind speed whilst the evaluation of the AEP by the Weibull distribution requires the integration of the cumulative distribution function that is a more demanding process in terms of computational effort.

4.2. Model calculation of the wake effect

Two analytical models, proposed by Jensen [22,23] and Katic [24] for the calculation of the wake effect, have been used in the studies analyzed in this review.

The model proposed by Jensen has been used in [53,56,58,60,64,67], and [69], while the Katic model has been applied to the optimal layout problem of WTs in [63,65,66,70,72,75,77] and [91].

According to Jensen [22,23], the wind-speed decay produced in the airflow when the wind passes through the rotor of a wind turbine, (see Fig. 4), is calculated by the expression:

$$u = u_0 \left[1 - \frac{2a}{\left(1+\alpha\left(\frac{d}{r_1}\right)\right)^2}\right] \tag{15}$$

where a is the axial induction factor or inflow factor that is related to the thrust coefficient, C_T, according to Eq. (17), d is the distance to the downwind WT, r_1 is the radius of the wake at the position of the downwind WT, u_0 is wind speed in free flow, and α is the entrainment constant calculated by the expression:

$$\alpha = -\frac{0.5}{\ln\left(\frac{z}{z_0}\right)} \tag{16}$$

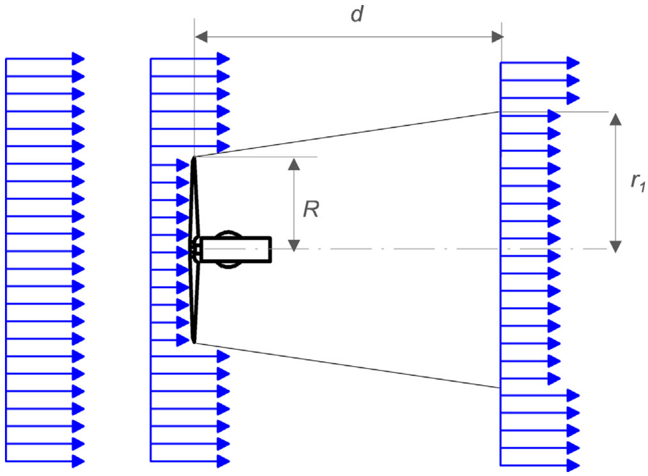

Fig. 4. Schematic representation of the wind speed field in the wake.

Table 2
Typical surface roughness lengths.

Type of terrain	Roughness length, z_0 (m)
Water surface	0.0002
Open farmland, few trees and buildings	0.003
Villages, countryside with trees and hedges	0.1
Cities, forests	0.7

where z is the turbine hub height and z_0 is the roughness length that depends on the type of terrain as shown in Table 2 [133].

According to Jensen [22] the thrust coefficient of the WT, C_T, and the radius of the wake downstream, r_1, are directly related to the axial induction factor, a, and the rotor diameter, R, using the Betz relations:

$$C_T = 4a(1-a) \tag{17}$$

$$r_1 = R\sqrt{\frac{1-a}{1-2a}} \tag{18}$$

The wake model proposed by Katic [24] takes the balance of momentums and the theory of Betz into account. The speed inside the wake is determined by the following equation:

$$u(d) = u_0\left(1-\left(1-\sqrt{1-C_T}\right)\left(\frac{D}{D(d)}\right)^2\right) \tag{19}$$

where D is the rotor diameter and $D(d)$ is the diameter of the downstream wake calculated by expression (20) as a function of the wake effect constant k_W.

$$D_W(d) = D + 2k_W d \tag{20}$$

The recommended values of the wake effect constant, k_W, are 0.075 in onshore facilities and 0.05 in case of an offshore wind farm [47].

Both the Jensen [22,23] and Katic [24] wake effect models require similar computational effort. However, the Katic model is the most widely accepted model by the wind energy industry, since it allows obtaining accurate results (in the case of non-complex terrains) using a relatively simple mathematical formulation.

4.3. Characteristics of the wind turbine: Power curve and thrust coefficient curve

The power output as a function of wind speed has been modelled using two separate approaches (see Fig. 5):

- The theoretical equation resulting from applying the laws of Betz and the momentum in the airflow passing through the surface swept by the blades of the WT (taking into account the limit of maximum rated power). This approach has been used in [53,56,58,61,63,64,67,69,75–77] and [70].
- The experimental curve of wind-speed power supplied by the WT manufacturer [65,66], and [72].

Another major feature of the WT to be considered is the thrust coefficient, C_T, since, as can be observed in expression (19), the wind speed decay in the wake depends on the thrust coefficient. To date, only [114], and [128] have considered a C_T value variable depending on wind speed in accordance with the experimental curve provided by the manufacturer, [17] proposes calculating the wake effect by means of a theoretical evolution of the C_T with the wind speed, while any remaining work considers a constant value. This decision is justified (especially in cases in which the wind speed has been modelled on the mean value), since, as shown in the example in Fig. 6, the experimental thrust coefficient remains at very similar values for a wide range of wind speeds (between about 4–13 m/s).

As can be observed in Figs. 5 and 6, the features of the wind turbine, i.e., wind power and thrust coefficient curves, differ when considering theoretical or experimental values. It is worth noting that considering a fixed value can lead to a significant error when evaluating the wake effect, since the lower the thrust coefficient the lower the wind speed deficit due to the wake effect. Therefore, this hypothesis may lead to underestimating the AEP.

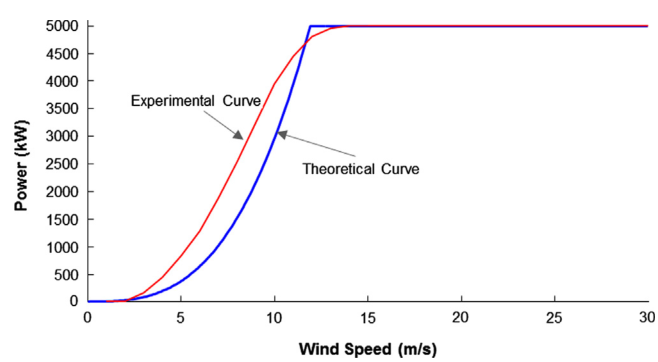

Fig. 5. Wind turbine experimental and theoretical power-speed curve.

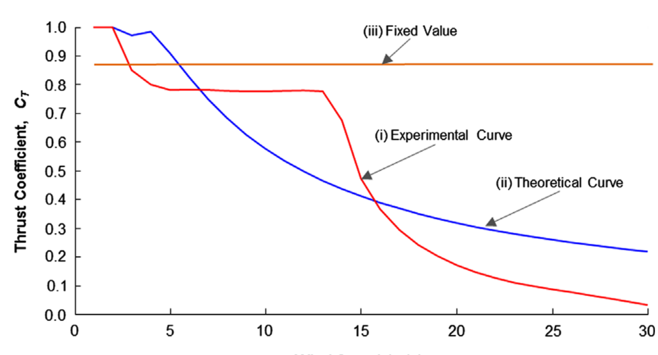

Fig. 6. Thrust coefficient curve: (i) experimental curve, (ii) theoretical curve, (iii) fixed value.

Table 3
Summary of main features of the work covered in the literature review.

	Mostetti et al.	Ozturk and Norman	Grady et al.	Castro et al.	Serrano et al.	Saavedra et al.	Messac et al.	Wan et al.	Kusiak and Song
Optimization method	GA	Greedy	.GA	GA	GA	GA	PSO	PSO	SPEA
Computational domain	Discrete	Discrete	Discrete	Discrete	Discrete	Discrete	Continuous	Continuous	Continuous
Forbidden zones	No	No	No	Yes	Yes	Yes	No	No	No
Investment limit	No	No	No	Si	Yes	No	No	No	No
Wake-effect model	Jensen	-	Jensen	-	Katic	Jensen	-	Jensen	Jensen
Thrust coefficient	0.88	-	0.88	-	0.88	-	-	0.88	0.8
Wind-rose sectors	36	8	36	1	8	16	-	36	24
Wind behaviour	Mean	Mean	Mean	Weibull	Weibull	Weibull	Mean	Mean	Weibull
Power curve	Theoretical	Theoretical	Theoretical	Experimental	Experimental	Theoretical	Theoretical	Theoretical	Theoretical
Electrical infrastructure design	No	No	No	No	Yes	Yes	No	No	No
Objective function	(1)	(2)	(3)	(4)	(4)	(4)	(6)	(5)	(5)

1—Minimize weighting relationship between Cost and AEP.
2—Maximize profit.
3—Minimize ratio of Cost–AEP.
4—Maximize *NPV.*
5—Maximize AEP.
6—Minimize standard deviation of *COE* divided by *COE*.

Nevertheless, as in the case of the simplified wind behavioural model, this assumption can be justified in those works with the objective of studying the performance of the optimization techniques.

5. Problem constraints

In order to address the problem in a realistic and flexible way, several authors have proposed restrictions inherent to the micro-positioning problem of WTs:

- Land available. All the research analyzed has considered the optimization of the layout of WTs over a finite area, and hence the position of all the WTs is limited by the limits of the plot.
- Forbidden zones. In [65–67] and [72], areas are proposed where no wind turbine can be placed. In this way, it is possible to take into account environmental constraints or plots of land with a complex shape.
- Maximum investment. [64–67] and [72], take into account the limitation of the maximum investment to be made if the investor has limited capital available to start the project.
- Maximum number of WTs. It is possible that the maximum number of WTs or the maximum rated power of the WF is limited by government rules. Therefore, in [57,62,65,66,72] and [75], the way this restriction affects the configuration of the wind farm is studied.
- Distance between wind turbines. The studies [63,67,70,75,76] and [88] take the constraint of minimum distance between WTs into account, since for technical reasons it is not recommended to place wind turbines too close to each other.
- Electrical infrastructure. In [66], the complete design of the wind farm is studied by incorporating the design of the electrical system and studying its influence on the layout of the WTs. This work therefore also includes constraints, such as forbidden areas that cannot be crossed by electrical lines and the capacity limit of power transmission of medium voltage (MV) and high voltage (HV) lines.

As can be seen, the objective of the problem constrains is to make the problem formulation as realistic as possible by taking into account the typical features of the wind power project. In general terms, adding realistic constrains to the problem involves, besides an increment in the complexity of the problem formulation, a higher degree of difficulty for the optimization process, since these constrains usually make the problem more discrete/discontinuous (as the search space becomes less continuous).

6. Optimization algorithms

As previously stated, the micro-siting problem of WTs cannot be solved by classic optimization techniques. Therefore, except in the case of [68], in which a fitted objective function for two WTs is optimized by a gradient search algorithm, the techniques most commonly used have been meta-heuristic optimization algorithms. In particular, the most widely used optimization method is that of GAs. Such techniques have been applied to the design of wind farms in [56,57,60,64–66] and [67]. GAs operate on a population of individuals [134–136]. Each individual is a potential solution to the problem and is typically encoded as a string of binary numbers as in the case of [56,57,60], and [64] although other codifications are also common, such as real numbers used in [64–66], and [67]. After generating the initial population, randomly or by a heuristic method such as in [67], the algorithm makes the population evolve sequentially and iteratively, by applying three operators: selection, crossover, and mutation.

The PSO algorithm was developed by Eberhart and Kennedy [137,138], based on an analogy of swarms of birds and fish schooling. The particles move through the hyper-dimensional search space. These techniques have been successfully applied to the problem described in this paper in work performed by Wan et al. [61,70], and Messac et al. [88], who all obtained satisfactory results over a continuous computational domain.

Greedy algorithms have been applied in the works of Aytun Ozturk and Norman [55] and Changshui et al. [69]. These techniques consist of sequentially introducing a new WT at the best position available in each iteration. In this way it is possible to quickly obtain a local optimum solution to the problem. Saavedra et al. [67] used a Greedy algorithm in order to obtain the initial population to be optimized by the GA.

Kusiak, et al. [63] proposed multi-objective optimization through an SPEA algorithm [139,140] by performing the optimization over a continuous computational domain and optimizing simultaneously the AEP and a penalizing function that takes into account the constrains of the problem.

The ant colony optimization algorithm [141,142] is based on the behaviour of ants in their search for food. Eroğlu and Seçkiner [75]

used an ACO algorithm based on a novel pheromone updating scheme over a continuous domain obtaining the optimal solution with a reasonable computational time.

Finally, further optimization methods used in other scientific publications are also featured: Wagner et al. [107] proposed a local search optimization method; Acero et al. [102] and Bilbao et al. [109] optimized the problem by simulated annealing; while Fredrich et al. [106] and Wagner et al. [107] proposed the covariance matrix adaptation evolution strategy (CMA-ES) as the optimization algorithm.

As it can be seen, in all cases meta-heuristics optimization techniques have been used due to the nature of the problem. GA has been the most widely used optimization method showing a proper performance. However, other techniques such as PSO, SPEA, ACO or CMA-ES have also been proved to be suitable methods to tackle this problem presenting, in some cases, additional advantages, e.g., considering a continuous domain or multi-objective optimization.

7. Key features

Table 3 shows a summary of the most relevant work analyzed herein on the problem of the optimal positioning of wind turbines, and highlights the main features concerning the objective function, production, and economic model of the wind-farm energy used in each study.

8. Conclusion

In this paper, a review has been carried out of the literature on earlier work on the problem of the optimal location of wind turbines. In general terms, from among the studies analyzed, two main trends are identified:

- Application of several optimization algorithms by optimizing a relatively simple economic model of a wind farm which take into account the energy production of wind farms and the costs calculated by using an empirical expression that considers economies of scale. GAs have been widely used to tackle this problem. Nevertheless, more recent work has shown good performance of other meta-heuristic algorithms, such as PSO, ACO, CMA-ES and SPEA, which additionally enable the optimization over a continuous domain (instead of the discrete domain used by the GA). It is also worth noting that various studies have optimized the problem by using greedy algorithms that allow a quick search for a local optimum. This strategy can provide acceptable solutions for the case where wind conditions are not uniform over the whole area covered.
- Development of realistic models of economic behaviour of wind farms. In this case the problem has been focused on modelling (and integrating into a global model of the wind farm) aspects, such as investment costs typically involved in wind farms, and costs of operation and maintenance. These include the design of the electrical installation, the network of access roads, and foundations. Within this trend, it is necessary to highlight the growing interest in analyzing the influence of the uncertainty associated with the input data on the design of the wind farm.

After studying the aforementioned work on this topic, it is possible to propose potential areas for future research:

- Most papers do not provide in-depth details about the computational cost required by each of the optimization methods and how their behaviour evolves as the size of the wind farm increases. As previously stated, the problem cannot be solved by classic optimization techniques; therefore most authors have proposed meta-heuristic methods in order to optimize this problem. The behaviour of these techniques is affected by the size of the solution space (in relation to the size of the WF). Therefore, as the size of the solution space increases, the parameters of the optimization algorithm should be tailored according to the complexity of the problem addressed. For instance, in the case of a GA, the population size and the convergence criterion should be adjusted to the dimensions of the problem. Large WFs would require such a great computational effort that the problem would be rendered virtually unfeasible under the current state of computer technology. Therefore, the development of efficient optimization techniques for large wind farms can prove highly useful in future studies.
- The model for calculating the energy produced by the wind farm can be the subject of future research, in particular, the calculation models of the wake effect. Several studies [143–146] have shown that the behaviour of these models in the case of complex terrain orography does not fit with sufficient accuracy to real production values. Therefore, the current trend in complex terrain focuses on the development of CFD models to evaluate the wake effect and energy produced. These models are based on the simulation of fluid behaviour using numerical methods, which require high computational effort. Therefore, the introduction of an analysis of the wake effect using CFD techniques in the WTs micro-sitting problem remains unfeasible with the current state of computer technology. Nevertheless, in the coming years, with the future development of computers, it will be an important factor to be considered.
- Project uncertainty. The economic behaviour of a wind farm is subject to a high level of uncertainty. Although there are some studies that have dealt with the uncertainty related to the behaviour of the wind, it is possible to extend this analysis to other variables of the problem and apply decision-making techniques so that the WF design is appropriate to such risk.
- Conflict of interest issues. Wind energy production can be affected by the presence of other nearby projects, or even WTs belonging to other owners of the plot of land [13]. This fact means that wind farm design needs to take into account the possible decisions of other developers. Decision making using game theory, combined with the optimization techniques analysed in this paper, can be a useful tool to achieve a proper design of the wind farm so that the risks associated with third-party decisions can be minimized.
- Environmental impact assessment. The consideration of factors such as environmental impact assessment as a result of the implementation of the wind farm is also an important factor which can be included in the optimal design tool for wind farms. In particular, factors such as noise or visual impact can be studied during the planning of wind farms. In this way, it would be possible to assess and mitigate the impact of the wind project on the environment.

Analysis of reliability of components. The economic performance of a wind farm is conditional on the reliability of its components. The effect of reliability has been taken into account in several works by introducing a coefficient of the availability of wind turbines based on typical values obtained in various studies [147,148]. However, the components of a wind farm can be subject to very different operating environments, depending on the local conditions at the placement of the component. In particular, the presence of nearby wind turbines produces an increase in turbulence in the airflow, and hence turbines located downwind are

subjected to higher fatigue stresses that affect the reliability of mechanical components.

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