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Bi-hierarchy Optimization of a Wind Farm Considering Environmental Impact

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Abstract—The high penetration of wind energy in electrical power systems presents challenges for all operators. For the wind farm (WF) planners, one of these challenges is optimizing its layout with a set of constraints. This paper proposes a bi-hierarchy optimization scheme to determine the capacity and layout of a grid-connected WF. The environmental impacts involved by the installation of a WF have been taken into consideration in the problem. The first-layer model optimizes the WF capacity and configuration with minimized comprehensive generation cost of wind energy and two sets of constraints. The sound pressure level (SPL) limit of the noise emitted by the wind turbines (WTs) is handled to be one of the constraints of the first-layer model. The second-layer model determines the generation schedule of other conventional generators. A Gaussian wake model is applied to calculate the effective wind speed for each WT. For the simulations, the WF is supposed to be integrated in the IEEE 30-bus test system. The wild goats algorithm (WGA) and the quadratic programming (QP) method are used to solve the problem. The simulation results validate the effectiveness of the proposed model and prove that environmental influences of WFs should not be ignored during the planning stage.

Index Terms—bi-hierarchy optimization, environmental effect, noise propagation, power flow, wake effect, wild goats algorithm, wind farm planning

NOMENCLATURE

B_{mn} (S)	Electrical susceptance of the line mn .
$C_{EC,i}^t$ (€/hr)	Emissions penalty of the i -th generator at the t -th hour.
$C_{gen,i}^t$ (€/hr)	Generation cost of the i -th generator at the t -th hour.
C_{wf} (MVA)	WF capacity.
C_{wf}^o (€/day)	WF daily operation & maintenance (O&M) cost.
C_{wf}^l (MVA)	Lower bound of the WF capacity.
C_{wf}^u (MVA)	Upper bound of the WF capacity.
C_{wt}^{unit} (M€/MW)	Unit cost of the WT.
C_{wt} (€/day)	WT daily equivalent investment.
C_e (€/day)	Power grid daily environmental penalty cost.
C_o (€/day)	Power grid daily operation cost.
d (%)	Discount rate.
d_r (m)	WT rotor diameter.
D (day)	Total days in one year.
E_{wf} (MWh)	WF expected daily energy production.

G_{mn} (S)	Conductance of the line mn .
h_r (m)	Noise receptors' height.
H (hr)	Total hours in one day.
L_{wf} (yr)	WF life time.
N_b	Total number of buses in the power grid.
N_{gen}	Total number of conventional generators in the power grid.
N_{ld}	Total number of bus loads in the power grid.
N_r	Total number of noise receptors.
N_t	Total number of WTs in the WF.
p_{mn}^l (MW)	Lower bound of the mn -th line active power flow.
p_{mn}^t (MW)	Active power flow of the mn -th line at the t -th hour.
p_{mn}^u (MW)	Upper bound of the mn -th line active power flow.
$P_{gen,m(i)}^l$ (MW)	Lower bound of the m -th (i -th) generator active power output.
$P_{gen,m(i)}^t$ (MW)	Active power output of the m -th (i -th) generator at the t -th hour.
$P_{gen,m(i)}^u$ (MW)	Upper bound of the m -th (i -th) generator active power output.
$P_{ld,m(j)}^t$ (MW)	Active load value of the m -th (j -th) bus at the t -th hour.
P_{loss}^t (MW)	Network loss at the t -th hour.
P_{wf}^l (MW)	Lower bound of the WF power output.
P_{wt}^r (MW)	Rated active power of the WT.
P_{wf}^t (MW)	Active power output of the WF at the t -th hour.
P_{wf}^u (MW)	Upper bound of the WF power output.
q_{mn}^l (MVar)	Lower bound of the mn -th line reactive power flow.
q_{mn}^t (MW)	Reactive power flow of the mn -th line at the t -th hour.
q_{mn}^u (MVar)	Upper bound of the mn -th line reactive power flow.
$Q_{gen,m}^l$ (MVar)	Lower bound of the m -th generator reactive power output.
$Q_{gen,m}^t$ (MVar)	Reactive power output of the m -th generator at the t -th hour.
$Q_{gen,m}^u$ (MVar)	Upper bound of the m -th generator reactive power output.

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$Q_{ld,m(j)}^t$ (MVar)	Reactive load value of the m -th (j -th) bus at the t -th hour.
Q_{wf}^t (MVar)	Reactive power output of the WF at the t -th hour.
R_s (MW)	Spinning reserve capacity.
r_r (m)	WT rotor radius.
SPL_{lim} (dB(A))	Upper limit of SPL .
$U_{m(n)}^l$ (kV)	Lower bound of the m -th (n -th) bus voltage.
$U_{m(n)}^t$ (kV)	m -th (n -th) bus voltage at the t -th hour.
$U_{m(n)}^u$ (kV)	Upper bound of the m -th (n -th) bus voltage.
z_0 (m)	Surface roughness length.
z_h (m)	WT hub height.
z_{ref} (m)	Wind speed measurement height.
δ_m^l (°)	Lower bound of voltage phase angle at the m -th bus.
δ_{mn}^t (°)	Voltage phase angle difference between the m -th and the n -th buses at the t -th hour.
δ_m^u (°)	Upper bound of voltage phase angle at the m -th bus.
λ (€/MW)	Network loss price.
ρ (€/MW)	Unit penalty price of pollutant emission.
ϕ (°)	WF power factor angle.

I. INTRODUCTION

WIND power is regarded as an essential component of the modern energy supply and has been widely developed during the past decades. The worldwide cumulative wind power capacity reached 539 GW by the end of 2018 [1] and is anticipated to exceed 760 GW by 2020 [2]. With the increasing penetration of wind power generation, wind energy plays a more and more essential role as an alternative of electrical generation in power systems. In view of this, the grid-connected WFs will have a huge influence on the electrical system operation. The load requirements and other generation sources' behavior will in turn have an impact on the determination of WF capacity and configuration. However, despite its general popularity, wind energy is facing boycotts in some countries due to potential environmental and health concerns that have caused increasing awareness for WF planners.

The optimization of the WF capacity and layout is a preliminary and important issue for WF designers and electrical network planners. Firstly, the active and reactive power output of a grid-connected WF will have a great impact on the power flow and will in turn influence the network losses and bus voltages. Secondly, the total power output of a WF is affected by the interaction among the WTs inside due to the phenomenon known as wake effect. This optimization problem is very complex and involves various economic costs and environmental effects. Many studies have been done in the WT optimal micro-siting problem since the pioneering works by Mosetti [3] and Grady [4]. In 2015, Long [5] proposed a two-echelon WF layout planning model in grid and Cartesian coordinates, solved by the random key genetic algorithm (RKGA) and the particle swarm optimization (PSO) algorithm. Hou put forward an offshore WF design method in 2015 [6] and a WF placement direction optimization and power dispatch strategy optimization in 2017 [7] respectively, both solved by

means of the PSO algorithm. In 2016, Yang [8] studied the optimization of a WF and its application to power system reliability analysis, solved by the PSO algorithm. In 2018, Wang [9] investigated the utilization of the differential evolution (DE) algorithm in the WF layout optimization problem and designed a novel encoding mechanism to efficiently tackle this problem. A multi-objective optimization of a WF with a WT selection method was proposed in [10], solved by means of the harmony search (HS) algorithm and non-dominated sorting genetic algorithm-II (NSGA-II). Other milestone works of WF optimization include the research done by Sisbot [11], Kusiak [12], González [13], Chen [14], Shamshirband [15] and Sorkhabi [16].

The previous studies present two important deficiencies. Firstly, the WF capacity or the number of installed WTs is always decided beforehand. To our knowledge, the combined optimization of WF capacity and configuration in the grid-connected scenario has not been addressed before. However, in practice, the WF capacity determination and the WTs layout planning have mutual interaction and require to be jointly optimized to realize a cost-effective WF. Secondly, the objective function usually targets to find the trade-off between the minimization of the WF's own cost and the maximization of the power generation. The system operation costs and the environmental impacts brought by a WF have seldom been considered which usually embody in the following two aspects: 1) The network losses, the generation costs and the pollutant emissions in the power grid are reduced due to the presence of a WF. 2) WFs' operation would make noises that influence the neighboring's health, both for human beings and animals [16][17]. Therefore, both the positive and negative environmental impacts caused by a WF should not be ignored during the planning stage.

In order to overcome the drawbacks in the existent practices, a bi-hierarchy optimization method, which has been justified to be a suitable means to solve optimization problems with hierarchical features [18] is brought forward in this paper. The bi-hierarchy optimization has been successfully applied in reactive power optimization problems [19], in the plug-in electric vehicles coordinated dispatch problem [20], in the offshore WF collector system planning [21], and in the tidal current farm optimization problem [22][23], *etc.*, and all these have shed light on the WF optimization problem.

This paper is organized as follows: in Section II, the power output of the WF is modeled; in Section III, the bi-hierarchy optimization model is proposed; Section IV introduces the optimization algorithm; Section V discusses the simulation results and the conclusions are exposed in Section VI.

II. MODELING OF A WF

A. WT Power Curve

Compared with a piecewise polynomial function, the Logistic function [24] expressed in (1) is non-piecewise and is closer to the real WT power curve. It is used to represent the WT power curve in this study.

$$P_{wt}(v) = P_{wt}^r \left(1 + \exp \left(\frac{2s(v_{ip}-v)}{P_r-P_{ip}} \right) \right)^{-1} \quad (1)$$

where $s = \frac{dP}{dv}\bigg|_{v=v_{ip}}$, P_{ip} and v_{ip} are the power and wind speed at the inflection point of the WT power curve.

B. Wake Model

The Gaussian wake model (Fig. 1) which has been justified can better describe the real wake, states that [25]:

$$\begin{cases} v_{x,r} = \left(1 - K(x) \exp\left(-\frac{r^2}{2\sigma^2}\right)\right) v_0 \\ K(x) = 1 - \sqrt{1 - \frac{C_T}{2\left(\frac{\sigma}{r_r}\right)^2}} \\ \sigma = \frac{r_x}{2} = \frac{r_r}{2} + \frac{\alpha}{2}x \end{cases} \quad (2)$$

where $v_{x,r}$ is the wind speed at distance x and radius r , σ denotes the characteristic width of the wake, $K(x)$ is an undetermined coefficient of x , C_T is the thrust coefficient and α is the entrainment constant which can be obtained from (3).

$$\alpha = \frac{0.56}{\ln \frac{z_h}{z_0}} \quad (3)$$

Fig. 1. Gaussian wake model [25].

In this model, the radius of the wake expands indefinitely due to the characteristic of the exponential function. Consequently, all WTs located downstream with respect to a given one are in the wake regardless of the distance between them and no WT will be partially in the wake of another WT [26].

C. WF Output Power Calculation

A rotation of coordinates is operated in advance to ensure the wind is always in front of the WTs. By using the method proposed in [26], for a given inflow wind velocity $\mathbf{v} = (v_0, \theta)$ with wind speed v_0 (m/s) and wind direction θ (°), the WTs' coordinates should be transformed from the original layout $[X, Y]$ to the new one $[X', Y']$ according to (4).

$$\begin{bmatrix} X' \\ Y' \end{bmatrix} = \begin{bmatrix} X \\ Y \end{bmatrix} \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \quad (4)$$

When the relative distances between WTs in the new coordinates are determined, the wind speed of the i -th WT ($i = 1, 2, \dots, N_t$), v_i can be calculated by (5) [26].

$$v_i = v_0 - \sqrt{\sum_{j=1}^{N_t} t_{ij} \Delta v_{ij}^2} \quad (5)$$

where t_{ij} is a binary variable that equals 1 when WT i is in the wake of WT j and 0 otherwise. Because in the Gaussian model, wake expands indefinitely, t_{ij} assumes the value of 1 provided that WT j is located in front of WT i for a given wind direction θ . Therefore, the velocity deficit only relies on the location of each WT inside the WF and the direction of the wind. Δv_{ij} is the wake deficit of the i -th WT caused by the j -th WT.

The power output of the i -th WT $P_{wt}(v_i)$ can be calculated according to (1). In this way, the total power output of the WF P_{wf} can be obtained according to (6).

$$P_{wf} = \sum_{i=1}^{N_t} P_{wt}(v_i) \quad (6)$$

A WF can be regarded as a PQ load bus [27][28] when integrated in a network. The WF total injected active power P_{wf} and reactive power Q_{wf} are calculated according to (6) and (7) respectively.

$$Q_{wf} = P_{wf} \tan\phi \quad (7)$$

where ϕ is the power factor angle of the WF.

III. BI-HIERARCHY OPTIMIZATION MODEL

When tackling complex optimization problems with multi-level variables, the bi-hierarchy method has two advantages over the uni-hierarchy optimization. Firstly, it remarkably degrades the computational scale and reduces the complexity of the developed model. Besides, it significantly relieves the loading on the communication network [18]. Fig. 2 shows the general framework of the WF bi-hierarchy optimization.

Fig. 2. Bi-hierarchy optimization framework.

The interaction mechanism between the first and the second layer models is as follows. The overall optimization of WF sizing and WT micro-siting is formulated by the first layer with the objective to minimize the comprehensive generation cost of wind power and decide the optimal WF capacity, WT number and layout. The second layer is nested in the first layer via procuring the optimal generation schedule of other generators in the electrical network and producing the minimum operation and environmental penalty costs for the first layer model. The generation schedule acquired from the second layer model is affected by the outcome of the first layer model including the scheme of WTs integration and placement. Also, the optimized results of the first layer model are related to the generation and

the environmental penalty costs obtained from the second layer model.

A. The First Layer Model

In order to optimize the WF capacity and layout with minimized comprehensive generation cost of wind energy, the first-layer problem is formulated as (8).

$$\begin{aligned} \min F_1(\mathbf{T}) &= \frac{C_{wt} + C_o + C_e}{E_{wf}} \\ \text{s. t.} \quad &\left\{ \begin{aligned} &\text{cstr.1} \quad \begin{cases} WB_x^l \leq T_x^l \leq WB_x^u \\ WB_y^l \leq T_y^l \leq WB_y^u \\ \sqrt{(T_x^i - T_x^j)^2 + (T_y^i - T_y^j)^2} \geq 6d_r \\ C_{wf}^l \leq C_{wf} \leq C_{wf}^u \\ SPL(\mathbf{T}, \mathbf{R}^k) \leq SPL_{lim} \\ i, j \in \{1, 2, \dots, N_t\}, i \neq j, k \in \{1, 2, \dots, N_r\} \\ N_t \in \{N_t^{min}, N_t^{min} + 1, \dots, N_t^{max}\} \end{cases} \\ &\text{cstr.2} \quad \begin{cases} P_{gen,m}^t + P_{wf}^t - P_{ld,m}^t - U_m^t \sum U_n^t (G_{mn} \cos \delta_{mn}^t + B_{mn} \sin \delta_{mn}^t) = 0 \\ Q_{gen,m}^t + Q_{wf}^t - Q_{ld,m}^t - U_m^t \sum U_n^t (G_{mn} \sin \delta_{mn}^t - B_{mn} \cos \delta_{mn}^t) = 0 \\ U_m^l \leq U_m \leq U_m^u, \delta_m^l \leq \delta_m \leq \delta_m^u \\ P_{gen,m}^l \leq P_{gen,m}^t \leq P_{gen,m}^u, Q_{gen,m}^l \leq Q_{gen,m}^t \leq Q_{gen,m}^u \\ P_{mn}^l \leq P_{mn}^t \leq P_{mn}^u, Q_{mn}^l \leq Q_{mn}^t \leq Q_{mn}^u \\ m, n \in \{1, 2, \dots, N_b\}, m \neq n \end{cases} \end{aligned} \right. \quad (8) \end{aligned}$$

where $\mathbf{T}=(T_x^i, T_y^i)$, $i = 1, 2, \dots, N_t$ represents the matrix of the WTs' coordinates, $\mathbf{R}^k=(R_x^k, R_y^k)$, $k = 1, 2, \dots, N_r$ denotes the matrix of the noise receptors' coordinates. F_1 is the generation cost of unit wind energy consisting of the daily equivalent investment C_{wt} , the operation costs C_o of the power grid and its environmental penalty cost C_e . The minimum and maximum numbers of WTs are calculated by (9).

$$N_t^{\min(\max)} = \text{round} \left(\frac{P_{wf}^{l(u)}}{P_{wt}^r} \right) \quad (9)$$

where *round* is the rounding function.

The constraints in the first-layer model are constituted in two parts.

Cstr.1 concerns: 1) the boundaries of the WF planning area, i.e. WB_x^l , WB_x^u , WB_y^l and WB_y^u ; 2) the minimum allowable distance between WTs; 3) the lower and upper bounds of the WF capacity, i.e. C_{wf}^l and C_{wf}^u ; 4) the *SPL* limit of the WF at each of the N_r receptors, which is constrained to be lower than 40 dB(A). This value was recommended by the World Health Organization (WHO) [29].

$SPL(\mathbf{T}, \mathbf{R}^k)$ is the equivalent continuous downwind octave-band *SPL* of the whole WF and it can be calculated according to (10).

$$SPL(\mathbf{T}, \mathbf{R}^k) = 10 \log \left(\sum_{i=1}^{N_t} \sum_{j=1}^8 10^{0.1(L_f^{(i,j)}(\mathbf{T}, \mathbf{R}) + A_f^{(j)})} \right) \quad (10)$$

where $L_f^{(i,j)}$ is the equivalent continuous downwind octave-band *SPL* at each receptor location computed for each sound source at each of the eight octave bands j with nominal mid-band frequencies (63 Hz-8 kHz) [30]. $A_f^{(j)}$ is the standard A-weighting coefficients [16].

SPL for each octave-band (L_f) can be written as in (11).

$$L_f = L_w + D_c - A_w(f) \quad (11)$$

where L_w is the octave-band sound power emitted by the noise source, D_c is the directivity correction for sources that are not omni-directional (D_c is set to be 0 in this study), $A_w(f)$ is the

octave-band attenuation. The detailed calculation procedures are available in [30].

An example from the Horns Rev I WF of the relationship between *SPL* and the distance from the sound source is shown in Fig. 3. It reveals that the WTs, when deemed as noise sources, should be located as far as possible from the receptors.

Fig. 3. The relationship between *SPL* (A-weighted) and the distance from the sound source [17].

Cstr.2 is the set of power flow constraints at the t -th hour including: 1) active and reactive power balances; 2) bus voltage magnitude and phase angle constraints; 3) regular generators' active and reactive power output constraints; 4) bus active and reactive power flow constraints.

C_{wt} stands for the WTs daily equivalent investment cost and can be derived by using (12).

$$C_{wt} = N_t C_{wt}^{unit} P_{wt}^r \frac{d(1+d)^{L_{wf}}}{((1+d)^{L_{wf}} - 1)D} \quad (12)$$

C_o is the total operation cost including the WF daily O&M cost, generation cost of other generators in the power grid and network loss cost. It can be calculated by (13).

$$C_o = C_{wf}^o + C_{gen}^o + C_{loss}^o \quad (13)$$

where C_{wf}^o is the WF daily O&M cost and can be calculated by (14).

$$C_{wf}^o = \frac{OPEX_{unit} \cdot C_{wf}}{D} \quad (14)$$

where $OPEX_{unit}$ (€/MW/yr) is the WF unit annual O&M cost.

C_{gen}^o can be obtained from the second-layer model.

C_{loss}^o is the network loss cost which is calculated by (15).

$$C_{loss}^o = \sum_{t=1}^H P_{loss}^t \lambda \quad (15)$$

where P_{loss}^t is the network loss at the t -th hour which can be computed by (16).

$$P_{loss}^t = \sum_{i=1}^{N_{gen}} P_{gen,i}^t + P_{wf}^t - \sum_{j=1}^{N_{ld}} P_{ld,j}^t \quad (16)$$

where $P_{gen,i}^t$ can be obtained from the second-layer model. P_{wf}^t can be acquired from the typical daily curves of wind speed and wind direction.

C_e is the pollutant emission penalty cost and can be formulated by (17).

$$C_e = \sum_{t=1}^H \sum_{i=1}^{N_{gen}} C_{EC,i}^t \quad (17)$$

C_o and C_e are both determined by the second-layer model and sensitive to the power output of the WF. The first and the second-layer models interact with each other by C_o and C_e .

E_{wf} is the expected daily energy production of the WF and can be estimated by (18).

$$E_{wf} = H \cdot \sum_{i=1}^{N_t} \int_{0^\circ}^{360^\circ} \int_{v_{in}}^{v_{out}} P_{wt}(v_i) \cdot JPDF(v, \theta) dv d\theta \quad (18)$$

where $JPDF(v, \theta)$ stands for the joint probability distribution function of wind speed and wind direction. v_{in} and v_{out} are the cut in and cut out wind speeds of the WT.

B. The Second Layer Model

The aim of the second layer model is to plan the generation schedule of other generators in the power grid. It is formulated as an optimal economic dispatching model given as (19).

$$\begin{aligned} \min F_2(\mathbf{P}_{gen}) &= \sum_{t=1}^H \sum_{i=1}^{N_{gen}} C_{gen,i}^t + C_{EC,i}^t \\ \text{s.t. } \begin{cases} P_{wf}^t + \sum_{i=1}^{N_{gen}} P_{gen,i}^t - \sum_{j=1}^{N_{ld}} P_{ld,j}^t = 0 \\ P_{wf}^t + \sum_{i=1}^{N_{gen}} P_{gen,i}^u - \sum_{j=1}^{N_{ld}} P_{ld,j}^t - R_s > 0 \\ P_{gen,i}^l \leq P_{gen,i}^t \leq P_{gen,i}^u \end{cases} \end{aligned} \quad (19)$$

$C_{gen,i}^t$ can be expressed as a quadratic function such as in (20) [31].

$$C_{gen,i}^t(P_{gen,i}^t) = a_{o,i} + a_{1,i}P_{gen,i}^t + a_{2,i}(P_{gen,i}^t)^2 \quad (20)$$

where $a_{o,i}$, $a_{1,i}$, $a_{2,i}$ (€/MW) are the cost coefficients of the i -th generator, determined according to the generators' attributes.

$C_{EC,i}^t$ is the penalty cost of pollutant emission at the t -th hour and can be expressed by (21).

$$C_{EC,i}^t(P_{gen,i}^t) = Pollut_i^t(P_{gen,i}^t) \cdot \rho_i \quad (21)$$

where ρ_i (€/MW) is the unit penalty price which can be derived according to the method in [31]. $Pollut_i^t$ is the amount of pollutant released by the i -th generator at the t -th hour, and can be evaluated by (22) [31].

$$Pollut_i^t(P_{gen,i}^t) = b_{o,i} + b_{1,i}P_{gen,i}^t + b_{2,i}(P_{gen,i}^t)^2 \quad (22)$$

where $b_{o,i}$, $b_{1,i}$ and $b_{2,i}$ (lb/MW) are the emission coefficients of the i -th generator.

The three constraints represent the power balance of the power grid, the spinning reserve capacity restriction and the generators' output power limitation. The optimal generation schedule can be decided by the second-layer model, and the components C_o and C_e in F_1 of the first-layer model can be accordingly obtained from the second-layer model.

IV. OPTIMIZATION ALGORITHM

A. The WGA

The WGA is a newly-developed evolutionary algorithm (EA) inspired by the climbing behavior of wild goats [32]. It possesses the features of mutation, swarm intelligence, memory-based and search in groups. The WGA is used to solve the first-layer model.

In the WGA, the initial values assigned to the variables are wgs , which denote wild goats. Each wg is a solution of the optimization problem.

$$wg_i = [\mathbf{x}_i, \mathbf{y}_i], \quad i = 1, 2, \dots, N_{wg} \quad (23)$$

where N_{wg} is the wild goats total number.

The evaluated value of each wg can be expressed as in (24).

$$F_1(wg_i) = F_1(\mathbf{x}_i, \mathbf{y}_i), \quad i = 1, 2, \dots, N_{wg} \quad (24)$$

The weight W_i of each wg can be calculated by (25).

$$W_i = \exp \left(-2 \frac{F_1(wg_i) - \min_j \{F_1(wg_j)\}}{\sum_{j=1}^{N_{wg}} (F_1(wg_j) - \min_j \{F_1(wg_j)\})} \right) \quad (25)$$

$i, j = 1, 2, \dots, N_{wg}$

The wgs with the highest value of W are selected as leaders of groups G .

$$\begin{cases} G_1 = \{wg_1, \dots, wg_{N_{G_1}}\} \\ \vdots \\ G_{N_g} = \{wg_{N_{G_{g-1}}+1}, \dots, wg_{N_f}\} \end{cases} \quad (26)$$

where N_g is the number of groups at the start of the algorithm, and $N_f = N_{wg} - N_g$.

Then after the procedures of: 1) movement within groups; 2) reevaluation; 3) groups' cooperation and mutation of young goats; 4) movement to form one group, the optimum solution is obtained until reaching the maximum termination It_{max} .

In procedure 1), the movement of wgs uses a vector v similar to the one used by the PSO algorithm.

The leaders' movement is determined by (27).

$v(t+1) = w \cdot v(t) + R \cdot rand \cdot (p(t) - wg(t)) + c(t)$ (27) where w and R are the inertia weight and the personal learning coefficient respectively. p is the best attempt and c is an auxiliary parameter. $rand$ is a random number, $rand \in [0, 1]$.

The followers' movement is determined by (28).

$$v(t+1) = w \cdot v(t) + R \cdot rand \cdot (p(t) - wg(t)) + W_{l_k}(t) \cdot rand \cdot (wg_{l_k}(t) - wg(t)) + c(t) \quad (28)$$

where k indicates the index of groups.

The update of each wg 's position is given by (29).

$$wg_i(t+1) = wg_i(t) + v_i(t+1), \quad i = 1, \dots, N_{wg} \quad (29)$$

In procedure 3), the cooperation of wgs is given by (30).

$$G_i = G_i + \left\{ wg_k | k \in j, \min_{wg \in j} \{W\} = W_k \right\} \quad (30)$$

The mutation of wgs uses an operator similar to that of the genetic algorithm (GA).

$$wg_i(t+1) = wg_i(t) + rand \cdot (rand - wg_i(t)) \quad (31)$$

The detailed description of the WGA can be found in [32].

B. The QP algorithm

The QP [33] is a gradient-based optimization algorithm using differentiating of the objective function and an iterative procedure which can only be used to solve the continuously differentiable function. QP is used to solve the second-layer optimization problem. Afterwards, C_o and C_e are acquired and sent to the first-layer model.

C. Solution Procedures of the Optimization Problem

The first and second-layer models are linked by the WF installed capacity and layout and generation schedule of other generators in the power grid. This can be better understood with the help of the flow chart in Fig. 4 of this bi-hierarchy optimization problem.

Fig. 4. Flow chart of the bi-hierarchy optimization.

V. CASE STUDY

A. Test System and Data Source

The WF to be optimized occupies a rectangle area and its basic information is given in Table I. The planning area of the WF is given in Fig. 5 where the red dots on the boundaries denote the noise receptors. In the WF layout planning stage, all the dwellings in the neighborhood are regarded to be potential noise receptors. Receptors No.1-8, marked in blue circles are in the eight typical directions (NW, N, NE, E, SE, S, SW, W).

Fig. 5. Planning area of the WF.

TABLE I
INFORMATION OF THE WF

Length (m)	Width (m)	L_{wf} (yr)	z_0 (m)	z_{ref} (m)	$\cos\phi$
6800	4800	25	0.0001	62	0.9
C_{wf}^l (MVA)	C_{wf}^u (MVA)	$OPEX_{unit}$ (€/MW/yr)	d (%)	N_r	h_r (m)
120	180	106	5.39	116	1.5

The WTs installed in the WF are of the type Vestas V80-2 MW, which were installed in Horns Rev I offshore WF. The parameters of V80 are given in Table II. The power output [34] and sound power emittance (L_w) [16] curves of this WT are given in Fig. 6.

Fig. 6. Relationship of (a) power output and (b) sound power emittance of V80-2MW at different wind speeds.

TABLE II
PARAMETERS OF VESTAS V80

d_r (m)	P_{wt}^r (kW)	v_{in} (m/s)	v_r (m/s)	v_{out} (m/s)
80	2000	4	15	25
z_h (m)	C_T	P_{ip} (kW)	v_{ip} (m/s)	s (kW · s/m)
100	0.2	1091.2	9.37	313.7514

The WF is supposed to be integrated in the IEEE 30-bus test system. The parameters of the generators in this system are given in Table III [22]. An exchange rate is used for the conversion of dollars to euros.

TABLE III
PARAMETERS OF THE GENERATORS

Bus No.	P_{gen}^l (MW)	P_{gen}^u (MW)	a_0	a_1	a_2	b_0	b_1	b_2
1	50	200	0	1.8	0.0032	22.983	-0.90	0.0126
2	20	80	0	1.5	0.0154	25.313	-0.10	0.0200
5	15	50	0	0.8	0.0552	25.505	-0.01	0.0270
8	10	35	0	2.8	0.0073	24.900	-0.005	0.0291
11	10	30	0	2.6	0.0221	24.700	-0.004	0.0290
13	12	40	0	2.6	0.0221	25.300	-0.0055	0.0271

The typical daily load curves can be derived as follows.

- Step 1. Obtain the profile of the daily load curve in daily peak load percentage (Fig. 7) from IEEE RTS [35].
- Step 2. Combine this normalized daily mean curve and the total original load of the power grid. A daily curve of the total load of the power grid can be derived.

Step 3. According to the proportion of each of the original bus load (Table IV), the daily load curve of each bus can be acquired.

TABLE IV
PARAMETERS OF LOADS

Bus No.	P_{ld} (MW)	Q_{ld} (MVar)	Bus No.	P_{ld} (MW)	Q_{ld} (MVar)	Bus No.	P_{ld} (MW)	Q_{ld} (MVar)
2	21.7	12.7	12	11.2	7.5	20	2.2	0.7
3	2.4	1.2	14	6.2	1.6	21	17.5	11.2
4	7.6	1.6	15	8.2	2.5	23	3.2	1.6
5	94.2	19	16	3.5	1.8	24	8.7	6.7
7	22.8	10.9	17	9	5.8	26	3.5	2.3
8	30	30	18	3.2	0.9	29	2.4	0.9
10	5.8	2	19	9.5	3.4	30	10.6	1.9

Fig. 7. Daily load curve profile in percent of daily peak (winter, weekday).

The real wind characteristics of Horns Rev I WF measured at $z_{ref} = 62 m$ are used. The *JPDF* of wind speed and direction is shown in Fig. 8. 0° is the direction of north, 90° is the direction of east, 180° is the direction of south and 270° is the direction of west.

Fig. 8. *JPDF* of wind speed and direction (01/June/1999-31/May/2002) [36].

The typical daily curves of wind speed and direction are given in Fig. 9, also measured at Horns Rev I WF.

Fig. 9. Wind daily curve (00:00-23:59, 01/Jan/2002) [36].

The parameters of the WGA are set as $N_{wg} = 120$, $N_g = 10$, $w = 0.7298$, $R = 1.5931$, $m = 0.85$, and $It_{max} = 250$.

B. Simulation Results

1) Comparison of Different Planning Models

The bi-hierarchy and the uni-hierarchy planning models are investigated in the WF optimization problem.

Model 1. The proposed bi-hierarchy optimization model using (8) and (19) is applied to determine the WF's optimal capacity and configuration in consideration of the power grid planning and operation costs.

Model 2. The uni-hierarchy optimization model is established by only taking the WT's investment cost in (8) into account, while the operation costs and pollutant emission penalty cost are not included and only $C_{str.1}$ in (8) is regarded. The capacity of the WF is preset as 160 MW.

The simulation results are shown in Table V.

TABLE V
SIMULATION RESULTS OF DIFFERENT PLANNING MODELS

Model	F_1 (€/MWh)	C_{wt}/E_{wf} (€/MWh)	$(C_o + C_e)/E_{wf}$ (€/MWh)	C_{wf} (MW)
Model 1	127.78	87.65	45.92	134
Model 2	140.03	84.23	55.80	160

It can be indicated from Table V, that in Model 1, the cost of system operation and pollutant emission penalty per unit WF output power takes up a considerable part of the total cost (around 34%). Therefore, C_o and C_e should not be omitted and the bi-hierarchy optimization is necessary for WF planning.

The integration of the WF in the electrical network relieves the power generation pressure of other traditional generators which emit considerable amount of pollutant gas. Wind energy, which is a substitute of traditional generation source, makes a great contribution to alleviating the air pollution problem and helps save remarkable expenditure on pollutant penalty cost.

2) Comparison of SPL-constrained and Unconstrained Cases

To investigate the impact of the inclusion of noise emission of the WF in the optimization problem, the cases with and without the *SPL* constraint are studied respectively. The simulation results are given in Fig. 10 and Table VI.

Fig. 10. Comparison of WF optimization with and without *SPL* constraint.

SIMULATION RESULTS OF CASES WITH AND WITHOUT SPL CONSTRAINT			
Case	F_1 (€/MWh)	Total power (MW)	Average <i>SPL</i> (dB(A))
With <i>SPL</i> constraint	127.78	61.32	37.52
Without <i>SPL</i> constraint	116.01	87.63	46.13

It can be inferred from Fig. 10 that the total number of the WTs installed without the *SPL* constraint ($N_t = 86$) is more than that with the *SPL* constraint ($N_t = 67$). There are many WTs installed on the boundaries of the WF when the *SPL* constraint is absent. This can be explained as follows: when there is no restriction of WF noise emittance, the aim of this optimization will simply become to produce utmost power and

to minimize the expenditure. When the SPL constraint is added, the value of the objective function F_1 increases 10.1% but the average SPL decreases 18.6%.

The SPL received by the receptors No.1-8 in Fig. 5 are shown in Fig. 11. Significant SPL reductions are observed when the SPL constraint is included and only in this case, the SPL limit ($SPL_{lim} = 40 \text{ dB(A)}$) can be satisfied by all the receptors. Therefore, the SPL constraint must be added in the WF planning to ensure all the residents living nearby are not affected by the noise produced by the WF.

Fig. 11. SPL received by the receptors with and without SPL constraint.

3) Comparison of the WGA and Other Optimization Algorithms

The WGA is compared with the GA and PSO algorithm in the WF optimization problem (case: Model 2). The codes of the algorithms are obtained from [37] and the simulations are carried out in Matlab 2018b, on a PC with an Intel(R) Dual-Core at 2.40 GHz processor and 8.0 GB of RAM. The parameters of the GA and PSO algorithms are set as in Table VII. Because the performances of EAs can vary greatly depending on initial settings, the population sizes ($nPoP$) and the maximum number of iterations (It_{max}) have the same values for each algorithm. Besides, the value of the personal learning coefficient c_1 in PSO is equal to R in (28). p_c and p_m are the cross-over and mutation rates in the GA respectively. c_2 is the global learning coefficient in the PSO.

Table VIII shows the optimization results of F_1 and runtime (RT) for the 10 trails. Fig. 12 compares the best results of each algorithm in the 10 times of simulations. It can be inferred that the WGA is the best optimization algorithm regarding the ability of searching for the optimal solution ($F_1=154.86, 145.33$ and 140.03 €/MWh for the GA, PSO and WGA respectively) as well as the convergence speed (220, 174 and 83 generations for the GA, PSO and WGA respectively). It is mainly because the WGA absorbs the advantages of many other optimization algorithms, such as the GA and PSO algorithm. In this way, the WGA has a better ability of randomly searching in the solution space of the objective function, independent of the features of the function.

TABLE VII

PARAMETERS OF THE GA AND THE PSO ALGORITHM

Parameter	$nPoP$	It_{max}	p_c	p_m	
GA	120	250	0.7	0.3	
Parameter	$nPoP$	It_{max}	w	c_1	c_2
PSO	120	250	0.7298	1.5931	2.0

TABLE VIII

TEN TIMES RESULTS OF RUNNING THE GA, PSO AND WGA

Algorithm Results	GA		PSO		WGA	
	F_1 (€/MWh)	RT (s)	F_1 (€/MWh)	RT (s)	F_1 (€/MWh)	RT (s)
1	156.01	1684	145.64	1578	141.70	1046
2	154.92	1593	145.87	1504	141.34	1109

3	155.13	1601	146.34	1631	140.98	1098
4	155.89	1587	146.01	1602	140.03	1073
5	154.99	1612	145.89	1595	142.05	1057
6	155.24	1633	147.01	1589	140.87	1113
7	154.86	1528	146.24	1613	141.04	1034
8	155.32	1534	146.78	1572	142.12	1086
9	154.89	1645	145.33	1622	143.21	1101
10	155.19	1580	145.91	1583	141.34	1043

Fig. 12. Convergence characteristics of the GA, PSO and WGA.

VI. CONCLUSION

The motivation of this paper is to propose a bi-hierarchy optimization framework for a grid-connected WF. The following conclusions can be drawn from the simulation results.

1) The penalty cost of pollutant emissions and the generation cost of the power grid are crucial in the sizing and configuration of a WF. Neglecting these costs will undervalue the profit induced by the connection of the WF to the power grid and the potential of wind energy will be inaccurately estimated. On this account, the bi-hierarchy optimization is more apt than the uni-hierarchy optimization for the grid-connected WF. However, in reality, WF developers will be separate entities from the grid owners or operators and will not be imposed with pollution penalties outside of their project. In view of this, overall cost optimization is possible where a single entity has control of all generating assets. Where separate owners exist, it is difficult to see the value in such a holistic optimization approach.

2) Overall, enforcing the SPL constraint has a slight effect on the cost of electricity but produces a substantial effect in reducing the noise disturbance to residents in the vicinity of the WF. Hence, it is rewarding to sacrifice a relatively small amount of economic benefit for significant improvements in eliminating the noise annoyance of the WTs.

3) The WGA is an effective EA to solve the WF optimization problem. It can search for the optimum solution with high efficiency and fast convergence speed.

The main contribution and novelty of this paper consists of planning the WF layout by considering the interaction with the electrical power system taking into account the fact that the capacity of the WF is not pre-determined as is the usual practice. It is optimized during the process instead. Also, both the positive and negative environmental impacts brought by the WF are taken into consideration. The extension of this optimization framework to onshore WFs and the inclusion of the WF cable layout in the second layer optimization model can be considered as future work.

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