Optimization of Decommission Strategy for Offshore Wind Farms

Hou, Peng; Hu, Weihao; Soltani, Mohsen; Zhang, Baohua; Chen, Zhe

Published in:
Proceedings of the IEEE Power & Energy Society General Meeting (PESGM), 2016

DOI (link to publication from Publisher):
10.1109/PESGM.2016.7741634

Publication date:
2016

Document Version
Accepted author manuscript, peer reviewed version

Optimization of Decommission Strategy for Offshore Wind Farms

Peng Hou, Weihao Hu, Mohsen Soltani, Baohua Zhang, Zhe Chen,
Department of Energy Technology
Aalborg University
Pontoppidanstraede 101, Aalborg DK-9220, Denmark
pho@et.aau.dk, whu@et.aau.dk, sms@et.aau.dk, bzh@et.aau.dk, zch@et.aau.dk

***Abstract*— The life time of offshore wind farm is around 20 years. After that, the whole farm should be decommissioned which is also one of the main factors that contribute to the high investment. In order to make a cost-effective wind farm, a novel optimization method for decommission is addressed in this paper. Instead of abandoning the foundations after the wind farm is running out of its life cycle, the proposed method can make good use of the existing facilities so that the cost of energy (COE) can be reduced. The results show that 12.93% reduction of COE can be realized by using the proposed method.**

***Index Terms*— offshore wind farm; optimization; decommission strategy, cost of energy (COE).**

Nomenclature

V_0 [m/s]	input wind speed at the wind turbine (WT)
V_x [m/s]	wind speed in the wake at a distance x downstream of the upstream WT
R_0 [m]	radius of the WT's rotor
R_x [m]	generated wake radius at x distance along the wind direction
$S_{overlap}$ [m^2]	affect wake region
C_t	thrust coefficient
k_d	decay constant
V_n [m/s]	wind speed at the blade of downstream WT considering the impacts of several upstream WTs
ρ [kg/m^3]	air density,
$C_{p,i}$	power coefficient of WT i
$P_{m,i}$ [MW]	mechanical power generated by WT i
v_i [m/s]	wind speed at WT i
$P_{tol,t}$ [MW]	total power production during interval t
T_E [day]	duration interval for energy yields calculation
T_t [h]	duration when the wind farm generating power of $P_{tol,t}$
$E_{tol,av}$ [MWh]	mean energy yields in one year
t [hour]	energy yields calculation time
(x_i, y_i), (x_k, y_k)	coordinate of WT i and k
$E_{tol,av}(x_i, y_i)$ [MWh]	mean energy yields in one year when the WTs' positions are (x_i, y_i)
A_p, B_p	coefficient of WT cost model
C_{WT}, C_f	cost coefficient of WT and foundation
x_{min}, y_{min}	minimum boundary of wind farm
x_{max}, y_{max}	maximum boundary of wind farm
d_{min}	minimal distance between any pair of WT
R	index of constraint function
N_{WT},N_f	total number of WTs and foundations
C	total number of penalty functions that should be used in the problem for unrestricted sea area
$\varphi(x_i,y_i)$	penalty function for WT i
w	inertia weight
l_1, l_2	learning factors
r_1, r_2	stochastic numbers which can generate some random numbers within [0, 1]
q_i^k, q_i^{k+1} [m]	position of ith particle at iteration k and k+1 respectively
v_i^k, v_i^{k+1} [m]	speed of ith particle at iteration k and k+1 respectively
Q_i^k [m]	best position of ith particle at iteration k
Q_g^k [m]	best position of all particles (the swarm) at iteration k
Q_i	best position found so far by the ith particle
Q_g	best position found so far by the swarm

This work has been (partially) funded by Norwegian Centre for Offshore Wind Energy (NORCOWE) under grant 193821/S60 from Research Council of Norway (RCN). NORCOWE is a consortium with partners from industry and science, hosted by Christian Michelsen Research.

I. Introduction

Offshore wind farms have advantages of higher energy efficiency and less impact on residents compared with onshore wind farms, however, the investment is high. In order to make more profits, many works have been done on optimization of offshore wind farm layout.

Due to the impact of wake effect, the wind speed reached at the downstream WTs will be reduced which incurs the energy losses of whole wind farm. To optimize the wind farm layout, two models are widely used. The first model is grid model which partition the whole wind farm into numbers of grids and the WT positions are selected from the center of some of these grids [1]-[5]. The other is coordinate model which used Cartesian coordinate system to represent the position of each WT [6]-[11]. The initial work to minimize the wake losses by placing the WTs in an optimized way is done by Mosetti et al who used genetic algorithm (GA) to optimize the WT layout [1]. Later, the authors of [2] improve this method by considering the possibility of installing more WTs in the same area. Many researches have been done on WT position optimization and the results were compared with the above two layouts [3]-[5]. The Monte Carlo algorithm was demonstrated to be outperformed by GA in solving this problem by assuming the wind direction is constant in [3] while [4] shows the advantages of using Intelligently Tuned Harmony Search algorithm for WT locating. In [5] a binary particle swarm optimization method with time-varying acceleration coefficients (BPSO-TVAC) is proposed and the obtained results are compared with other 5 meta-heuristic algorithms. The above methods were proved to be effective in increasing the power production, however, some possible solutions have already been neglected using grid model. The layout was expected to be further optimized by giving WTs more freedom to move within predefined area.

The first paper that used coordinate model to solve wind farm layout optimization problem (WFLOP) was addressed in [6]. Several WTs are optimized placed within a predefined circular shape wind farm. Similarly, [7] used colony optimization algorithm to solve the WFLOP and was demonstrated to be outperformed than [6]. A particle filtering approach was presented in [8] and the optimized layout was compared with the obtained layout in [6] and [7]. In addition to heuristic optimization, some attempts to use mathematical programming to solve WFLO problem were done in [9]-[11]. In [9], a random search (RS) algorithm was proposed which showed better performance by GA on computational time, moreover, the RS algorithm was also applied to design the Horns Rev I wind farm layout so that the energy yields can be increased. Also, Horns Rev I wind farm layout was selected as the benchmark and compared with the optimized layout obtained by sequential convex programming in [10]. Since the WFLOP is non-convex, global optimal solution cannot be guaranteed. In order to get an even near optimal solution, a mathematical programming method was adopted in [11] which used heuristic method to set an initial layout then used nonlinear mathematical programming techniques to get a local optimal solution.

As it is known, the life time of offshore wind farm is around 20 years [12]. After that, the WT cannot be used. The above works focused on maximizing the energy yields of wind farm without considering the decommission cost. In consideration of marine ecological environment and ensure the safety of navigation and other marine function, offshore wind farm should be decommissioned after stop production [13], however, the foundation of WT can still be used at that time. It is possible to use the existing foundations to establish a new wind farm so that the cost of decommission as well as the cost of installing new WTs can both be saved.

In this paper, a new decommission strategy is proposed which can reduce the cost of energy of the wind farm compared with the cost of establishing a new one. Instead of abandoning the foundations, new WTs can be installed on the original location. In consideration of the reduction of the foundation intensity after the wind farm life cycle, smaller WTs were selected to install on the original place. In order to have the same wind farm capacity, more WTs were elected on new locations and the locations were decided using adaptive PSO (APSO). A regular shape reference wind farm is chose as the study case and the result show that the proposed method is an effective way to reduce the cost of energy.

The paper is organized as follows. In Section II, the wind farm models are proposed at first. Followed by which is the objective function. The methodology is discussed in Section III. The simulation results and analysis are presented in Section IV and Conclusions are given in Section V.

I. Modelling of Wind Farm

In this section, the model of calculating energy yields considering wind speed deficit is introduced at first. Then the cost model and objective function are specified.

A. Wake Model

In this paper, Jensen model is selected to estimate the wind speed deficit. The analytical equations for calculating the wake velocity are in the following [14].

$$V_x = V_0 - V_0 \left(1-\sqrt{1-C_t}\right)\left(\frac{R_0}{R_x}\right)^2 \left(\frac{S_{overlap}}{S_0}\right) \tag{1}$$

$$R_x = R_0 + k_d\, x \tag{2}$$

The decay constant, k_d, describes the feature of the wake expansion, the recommended value for offshore environment should be 0.04 [14].

The above equations described how to calculate the wind speed behind one WT. The interaction of WTs within whole wind farm could also be described based on Katic et al's 'sum of squares of velocity deficits' method. The analytical equation is as follow [15]:

$$V_n = V_0 [1-\sqrt{\sum_{i=1}^{N}[1-\left(\frac{V_i}{V_0}\right)]^2}\ ] \tag{3}$$

The energy yields calculation considering variation of both wind velocity and wind direction has been done in a previous work. The detailed information can be seen in [16].

B. Energy Production of Offshore Wind Farm

In [17], the power extracted by individual WT is given as:

$$P_{m,i} = 0.5\rho C_{p,i} \pi \mathrm{R}^2 v_i^3 / 10^6 \tag{4}$$

By assuming a maximum power point tracking (MPPT) control strategy [18], the power production of each WT can be found by (4). The velocity at each WT is related to the WTs' positions (x_i, y_i). Hence, the total power production that generated by the WTs can be written as:

$$P_{tol} = \sum_{i=1}^{N} P_{m,i}(x_i, y_i) \tag{5}$$

Considering (1) to (5), the energy yields of the wind farm can be rewritten as:

$$E_{tol,av} = \frac{\sum_{t=1}^{T_E}\left(P_{tol,t}\right)T_t}{T_t T_E} 8760 \tag{6}$$

C. Cost Model

In this paper, the cost of WT which includes a 33kV transformer is set up according to its rated power. The mathematical equations can be written as [19]:

$$C_{\mathrm{WT}} = A_p + B_p \mathrm{P}_{\mathrm{rated}} \tag{7}$$

In this model, the cost of the WT is assumed to be increased linearly and the cost of foundation for each WT is 6.075 MDKK, which is assumed independent of water depth and size and type of WT [19].

D. Objective Function

In this work, the performance of the new wind farm using existing foundations will be compared with the ordinary one based on the evaluation index, cost of energy (COE) as follow:

$$\text{Obj:} \qquad \min(COE) = \frac{E_{tol,av}}{C_{WT} N_{WT} + C_f N_f} \tag{8}$$

$$\text{Contraints:} \qquad x_{\min} \le x_i \le x_{\max}, i \in (1, \mathrm{N}_{WT}) \tag{9}$$

$$y_{\min} \le y_i \le y_{\max}, i \in (1, \mathrm{N}_{WT}) \tag{10}$$

$$\mathrm{F}_r(\mathrm{x}_i, \mathrm{y}_i) = \sqrt{(\mathrm{x}_i - \mathrm{x}_k)^2 + (\mathrm{y}_i - y_k)^2} - d_{\min} \ge 0, \forall i \ne k \tag{11}$$

II. METHODOLOGY

Presently, heuristic algorithms are widely used in solving the non-linear problem. In this paper, APSO is selected as the optimization method. The theory and the optimization procedure are presented in the following.

A. PSO

The PSO algorithm was firstly proposed by Kennedy and Eberhart [20] in 1995. As one of the evolutional algorithms, it has a good performance of finding a near optimal solution for the nonlinear optimization problem. The global version PSO (GPSO) can be expressed in following equations [21].

$$v_i^{k+1} = wv_i^k + l_1 r_1 \left(Q_i^k - q_i^k\right) + l_2 r_2 \left(Q_g^k - q_i^k\right) \tag{12}$$

$$q_i^{k+1} = q_i^k + v_i^{k+1} \tag{13}$$

In PSO, the possible solutions (particles) will be coded into swarm and the size of swarm means the number of the particles, in other words, the number of possible solutions in a swarm is decided by the swarm size. As can be seen in (12), there are three parts. The first part represents the velocity of previous particle. A larger w ensures a stronger global searching ability while smaller w ensures the local searching ability. The other two parts are used to ensure the local convergence ability of the algorithm. Hence, the final result is sensitive to the setting of the control parameters (l_1, $l_2$and w). In order to reduce the sensitivity of final result to control parameters, many works have been done on the parameter control methods for w which can be concluded into two categories [22]: simple rule based parameter control [23]-[26] and adaptive parameter control strategy [27]. The first strategy indicate that the PSO performance can be improved by using linear, non-linear or fuzzy rule inertia weight while the other introduce evolutionary state estimation (ESE) technique [28] to further improve the performance of PSO. In this project, the WT positions were decided using the method in [27] .

B. Penalty Function

The heuristic algorithm as PSO can be used to solve the unconstrained optimization problem within the predefined area. In this case, (9) and (10) can be satisfied by PSO, however, (11) can be violated if no specific condition are defined. Conversely, if the particle is limited to follow (11) then the particles might be out of predefined boundary. In order to ensure the feasibility of the solution and simplify the numerical calculation, a penalty function method is used and defined as follow:

$$\phi(\mathrm{x}_i, \mathrm{y}_i) = \left|\min\left\{0, \mathrm{F}_r(\mathrm{x}_i, \mathrm{y}_i)\right\}\right| \tag{14}$$

Then, the objective function for unrestricted sea area wind farm layout optimization can be rewritten as:

$$max(\mathrm{COE} - \mathrm{PF}\sum_{i=1}^{C} \phi(\mathrm{x}_i, \mathrm{y}_i)) \tag{15}$$

The penalty function (11) represents the distance between the infeasible solution and the feasible region. $\varphi(x_i, y_i) = 0$ means that all the WTs' positions are found within the predefined area, F, in other words, the solution is feasible, while $\varphi(x_i, y_i) > 0$ indicates that some WTs' positions are out of construction area boundary. By using this method, (11) can be easily realized. The advantage of using penalty function is that the constrained optimization problem could be transformed into an unconstrained one so that the computational time can be reduced. In this paper, the penalty factor, *PF*, is determined as 1000. The value of this factor is selected by trial and error.

C. Optimization Framework

The optimization framework is shown in Fig.1.

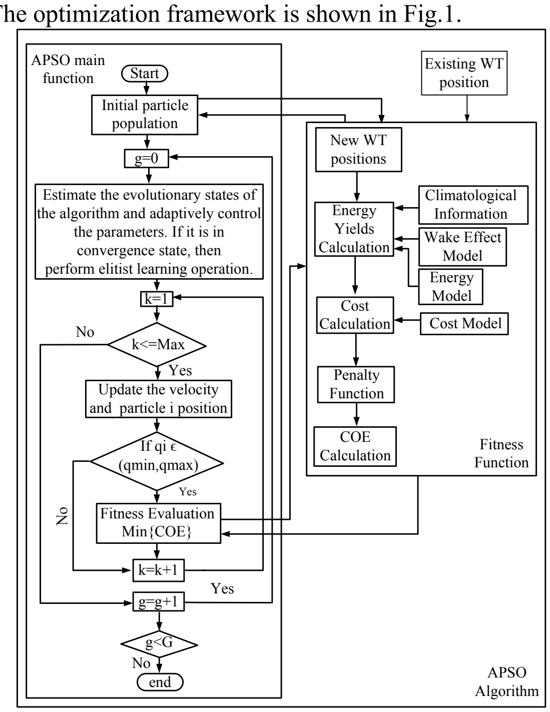

Figure. 1. Optimization flowchart based on APSO

The parameters of APSO are initialized in the first step. The existing WT and the new optimized WT positions will be integrated in Fitness Function and then the energy yields as well as the cost was calculated based on this wind farm layout. The penalty function will be used to ensure (11). After that, the COE will be calculated based on (4)-(8). The first calculated COEs as well as the corresponding particles (solutions) will be saved as the initial particle population which is the basis for comparison later. Then the particles will be updated and transferred into the fitness function by following the same procedure. The calculated result can be obtained and send out to the Fitness Function for comparison. Or it may stop if the maximum iteration is reached. Finally, a series of new installed WT positions will be decided.

Climatological information: The data is obtained from the work of the Norwegian Meteorological Institute [29], in which the wind speeds are sampled per 3 hours. For convenience of calculation, the raw data is formulated into a wind rose which is used to calculate the energy production over a year.

II. CASE STUDY

The simulation is implemented on the platform of Matlab software. One study case was adopted to verify the feasibility of the proposed method.

A. Scenario I: Rebuild on the Original Locations

The reference wind farm was established with 80, Vestas V80-2.0 MW (80m rotor diameter) [30] WTs which can be seen in Fig. 2. The total power capacity is 160MW. The locations of WTs are predefined within a 7D*7D regular shaped wind farm which means that the distance between each two WTs are 7 rotor diameters.

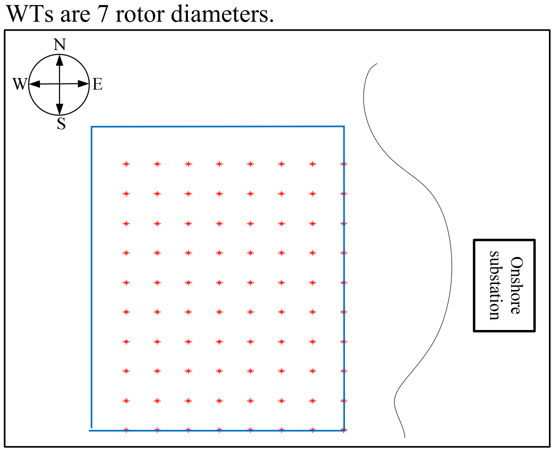

Figure. 2. Reference wind farm layout

The red stars show the WT positions while the blue line is the boundary for installing new WTs to rebuild the wind farm. Monopile foundation was adopted since the average water depth is assumed to be 10m. Since the design of WT has been developed during the decades of wind farm operating period, the present 2MW WT which has a lower cut-in speed can generating more power when the incoming wind speed is lower compared with the old version WT. Hence, the wind farm was rebuilt using the original locations with 2MW Vestas V90-2.0MW WT [31]. Since the foundation has been used for more than 20 years, strengthen cost is required. It is assumed that the cost for strengthening foundation is 10% of the foundation cost.

B. Scenario II: Decommision Optimization for Reference Wind Farm Wind Farm

In this work, the existing foundation will be used. For safety consideration, the Vestas V90-1.8MW WT [31] will be installed on the original place instead of 2MW WT. In order to have the same power capacity as original one has. 9 WTs will be installed and the new installed WT positions will be optimized considering the wake effect using APSO. Since smaller WTs are adopted in this case. The cost of strengthening foundation is assumed to be only 5%. The optimized layout is shown in Fig. 3.

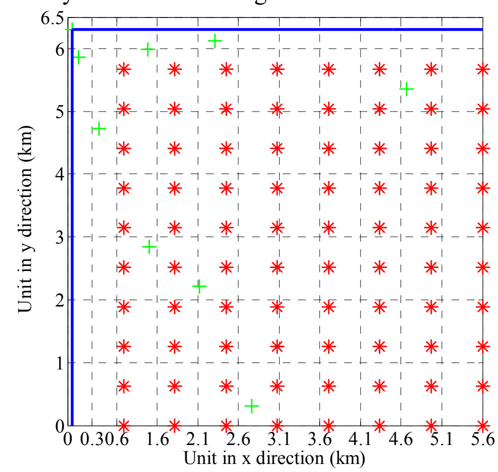

Figure. 3. Optimized wind farm layout

In Fig. 3, the red stars showed the original WT which has been replaced using 1.8 MW WTs while green plus indicated the nine new installed WT positions. The optimized WT positions are found by APSO and the fitness value corresponds to each iteration is illustrated in Fig. 4.

TABLE I. RESULTS COMPARISON

	Benchmark	Scenario I	Scenario II
Costs of WTs (MDKK)	991.44	991.44	982.15
Costs of renovation/bulid foundations (MDKK)	600	48.6	79.0
Total cost	1591.4	1040.04	1061.2
Energy yields (GWh)	764.90	764.90	806.32
CoE (DKK/MWh)	2080.5	1359.7	1316.1

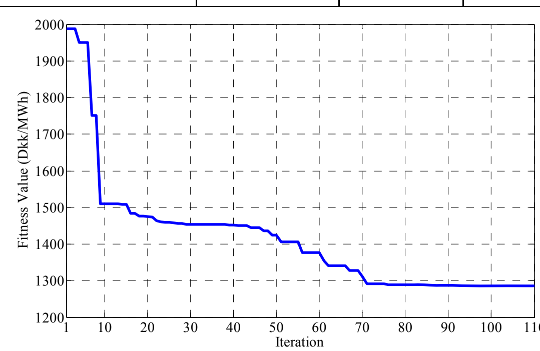

Figure. 4. Fitness Value corresponds to each iteration

In Fig. 4, the fitness value was stabilized around 810 after 90th iteration using APSO algorithm. In Table I, the benchmark is the common way of decommissioning which rebuild all the foundations on original place. It can be seen that the total cost is decreased by 33.32% using proposed method compared with benchmark while the cost will be increased by 2.03% compared with scenario I, however, by installing 9 more WTs with optimized locations, the total energy yields can be increased by 5.42% compared with benchmark and scenario I which resulted in the 36.47% and 3.21% reduction of COE at last.

III. Conclusions and Future Work

The offshore wind farm will be decommissioned in order to protect marine ecological environment after approximately 20 years' operation. This is mainly due to the fact that the WT cannot be used after this period. However, the foundation is always overdesigned. In order to make best use of the foundation and save the investment, a new decommission strategy is proposed in this paper. Instead of paying for abandoning the foundations, a new wind farm can be established using the original foundations. From simulation results, it can be seen that the decommission strategy can help reduce the cost of energy a lot (14.94% in the study case) and by merely installing 9 more WTs, the energy yields of whole wind farm can be significantly increased by 17.20%. The potential value of this method will not merely on foundations since the life time of parts of the WTs, such as tower body can also be longer than 20 years. The recycling idea in offshore wind farm proposed in this paper could show more commercial benefits in future.

Acknowledgment

Authors would like to thank Norwegian Centre for Offshore Wind Energy (NORCOWE) under grant 193821/S60 from Research Council of Norway (RCN).

References

[1] Mosetti G, Poloni C, Diviacco B., "Optimization of wind turbine positioning in large wind farms by means of a genetic algorithm," Journal of Wind Engineering and Industrial Aerodynamics. vol. 51(1), pp.105-116, 1994.

[2] S. Grady, M. Hussaini, and M. Abdullah, "Placement of wind turbines using genetic algorithms," Renewable Energy, vol. 30, no. 2, pp. 259 – 270, 2005.

[3] G. Marmidis, S. Lazarou, E. Pyrgioti, "Optimal placement of wind turbines in a wind park using Monte Carlo simulation," Renewable Energy, 33 (7) (2008), pp. 1455–1460.

[4] Narasimha Prasad Prabhu, Parikshit Yadav, Bhuneshwar Prasad and Sanjib Kumar Panda, "Optimal placement of off-shore wind turbines and subsequent micro-siting using Intelligently Tuned Harmony Search algorithm," Power and Energy Society General Meeting (PES), 2013 IEEE, pp. 1-7, Vancouver, BC, Jul. 2013.

[5] Sittichoke Pookpunt, Weerakorn Ongsakul, "Optimal placement of wind turbines within wind farm using binary particle swarm optimization with time-varying acceleration coefficients," Renewable Energy, Vol. 55, pp. 266-276, Jul. 2013.

[6] B Saavedra-Moreno, S Salcedo-Sanz, A Paniagua-Tineo, L Prieto, A. Portilla-Figueras, "Seeding evolutionary algorithms with heuristics for optimal wind turbines positioning in wind farms," Renewable Energy, vol. 36, pp. 2838–2844, 2011.

[7] S. Chowdhury, J. Zhang, A. Messa, L. Castillo, "Optimizing the arrangement and the selection of turbines for wind farms subject to varying wind conditions," Renew Energy, vol. 52, pp. 273–282, 2013.

[8] C.Wan, J.Wang, G. Yang, H. Gu, and X. Zhang, "Wind farm micro-siting by Gaussian particle swarm optimization with local search strategy," Renewable Energy, vol. 48, pp. 276–286, 2012.

[9] Feng, J.; Shen, W.Z., "Solving the wind farm layout optimization problem using random search algorithm," Renewable Energy, vol. 78, pp. 182–192, Jun. 2015.

[10] Jinkyoo Park, Kincho H. Law, "Layout optimization for maximizing wind farm power production using sequential convex programming," Renewable Energy, vol. 151, pp. 182–192, Aug. 2015.

[11] B. Pérez, R. Mínguez, R. Guanche, "Offshore wind farm layout optimization using mathematical programming techniques," Renew Energy, vol. 53, pp. 389–399, 2013.

[12] M. Zhao, Z. Chen, J. Hjerrild, "Analysis of the behaviour of genetic algorithm applied in optimization of electrical system design for offshore wind farms," Proc. Of the 32nd IEEE Conference on Industrial Electronics, pp. 2335–2340, 2006.

[13] Fei Wu, Xu Jia, Jiali Sun, Chunjie Yu, Hongsheng Ci, "Offshore oil and gas platform decommissioning research," OCEANS 2014 , Taipei, pp. 1-4.

[14] P. Beaucage, M. Brower, N. Robinson, and C. Alonge, "Overview of six commercial and research wake models for large offshore wind farms," in Proc. Eur. Wind Energy Assoc. (EWEA'12), Copenhagen, Denmark, 2012, pp. 95–99.

[15] Fernando Port´e-Agel, Yu-TingWu, Chang-Hung Chen, "A Numerical Study of the Effects of Wind Direction on Turbine Wakes and Power Losses in a large Wind Farm," Energies, vol. 6, pp. 5297-5313, MDPI, 2013.

[16] Peng Hou, Weihao Hu, Soltani, Mohsen, Zhe Chen, "Optimized Placement of Wind Turbines in Large Scale Offshore Wind Farm using Particle Swarm Optimization Algorithm," IEEE Transactions on Sustainable Energy, Vol. PP, Nr. 99, 2015.

[17] Javier Serrano Gonzáleza, Angel G. Gonzalez Rodriguezb, José Castro Morac, Jesús Riquelme Santosa, Manuel Burgos Payana, "Optimum Wind Turbines Operation for Minimizing Wake Effect Losses in Offshore Wind Farms," Renewable Energy, Vol. 35, Issue 8, pp. 1671-1681, Aug. 2010.

[18] Wei Qiao, "Intelligent mechanical sensorless MPPT control for wind energy systems," Power and Energy Society General Meeting, 2012 IEEE, pp. 1-8, San Diego, CA, Jul. 2012.

[19] S. Lundberg, "Performance comparison of wind park configurations," Department of Electric Power Enginering, Chalmers University of Technology, Department of Electric Power Enginering, Goteborg, Sweden, Tech. Rep. 30R, Aug. 2003.

[20] Kennedy, J., Eberhart, R., "Particle swarm optimization," Proc. IEEE Int. Conf. Neural Networks, pp. 1942–1948, Apr. 1995.

[21] Kennedy, J., "The particle swarm: social adaptation of knowledge," Proc. IEEE Int. Conf. Evolution of Computing, Indianapolis, IN, pp. 303–308, 1997.

[22] Mengqi Hu, Wu, T., Weir, J.D., "An adaptive particle swarm optimization with multiple adaptive methods," IEEE Transactions on Evolutionary Computation, Vol. 17, pp. 705-720, 10 Dec. 2012.

[23] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in Proc. Congr. Evol. Comput., 1999, pp. 1950–1955.

[24] B. Jiao, Z. Lian, and X. Gu, "A dynamic inertia weight particle swarm optimization algorithm," Chaos, Solitons Fractals, vol. 37, pp. 698–705, Aug. 2008.

[25] Y. Shi and R. C. Eberhart, "Fuzzy adaptive particle swarm optimization," in Proc. Congr. Evol. Comput., 2001, pp. 101–106.

[26] R. C. Eberhart and Y. Shi, "Tracking and optimizing dynamic systems with particle swarms," in Proc. Congr. Evol. Comput., 2001, pp. 94–100.

[27] Z.-H. Zhan, J. Zhang, Y. Li, and H. S.-H. Chung, "Adaptive particle swarm optimization," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 39, no. 6, pp. 1362–1381, Apr. 2009.

[28] J. Zhang, H. S.-H. Chung, and W.-L. Lo, "Clustering-based adaptive crossover and mutation probabilities for genetic algorithms," IEEE Trans. Evol. Comput., vol. 11, no. 3, pp. 326–335, Jun. 2007.

[29] Birgitte R. Furevik and Hilde Haakenstad, "Near-surface marine wind profiles from rawinsonde and NORA10 hindcast," Joanal of Geophysical Research, Vol. 117, 7 Dec. 2012.

[30] "Never Installed Turbine-technical brochure," Blue Planet Wind NV, Sint Aldegondiskaai 18, 2000 Antwerpen, Belgium.

[31] "V90-1.8/2.0 MW Maximum output at medium-wind and low-wind sites," Vestas Wind Systems A/S, Alsvej 21, 8940 Randers SV, Denmark.