Article

Wind Farm Layout Optimization Using a Metamodel and EA/PSO Algorithm in Korea Offshore

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Abstract: This paper examines the solution to the problem of turbine arrangement in offshore wind farms. The two main objectives of offshore wind farm planning are to minimize wake loss and maximize annual energy production (AEP). There is more wind with less turbulence offshore compared with an onshore case, which drives the development of the offshore wind farm worldwide. South Korea's offshore wind farms, which are deep in water and cannot be installed far off the coast, are affected by land complex terrain. Thus, domestic offshore wind farms should consider the separation distance from the coastline as a major variable depending on the topography and marine environmental characteristics. As a case study, a 60 MW offshore wind farm was optimized for the coast of the Busan Metropolitan City. For the analysis of wind conditions in the candidate site, wind conditions data from the meteorological tower and Ganjeolgot AWS at Gori offshore were used from 2001 to 2018. The optimization procedure is performed by evolutionary algorithm (EA) and particle swarm optimization (PSO) algorithm with the purpose of maximizing the AEP while minimizing the total wake loss. The optimization procedure can be applied to the optimized placement of WTs within a wind farm and can be extended for a variety of wind conditions and wind farm capacity. The results of the optimization were predicted to be 172,437 MWh/year under the Gori offshore wind potential, turbine layout optimization, and an annual utilization rate of 26.5%. This could convert 4.6% of electricity consumption in the Busan Metropolitan City region in 2019 in offshore wind farms.

Keywords: offshore wind farm layout optimization; park wake model; metamodel; evolutionary algorithm; particle swarm optimization; Korea offshore

1. Introduction

Diversifying energy sources and securing energy supplies are key energy strategy targets for many countries [1]. Due to climate change, wind energy has become more and more important for power generation without carbon dioxide emissions [1]. Offshore wind power is a good opportunity for South Korea, providing opportunities to accelerate power generation without the use of fossil fuels or nuclear power generation [2]. In order to achieve the "renewable energy 3020" goal of 20% renewable energy in the power mix by 2030, South Korea has aimed to build 12 GW of new offshore wind power generation capacity by the end of the decade [2].

The world's first offshore wind farm was built in 1991 in Vindeby, southeast of Denmark. After 25 years of operation, the concept of offshore wind power has been proven to be effective. Korea began commercial operations of offshore wind farms on Jeju Island when the first generation of offshore wind farms disappeared. Difficulties still exist related to marine meteorological and geographical characteristics (e.g., around Jeju Island and the sudden change of water depth in the East Sea coast), acceptance by local residents, investment costs related to specific military regulations, and long-term economic assessments. In order to overcome these difficulties and secure their economic viability, it is imperative to optimize the layout of offshore wind farms.

Approaches to the optimal placement of early wind turbines often did not reflect practical conditions in the calculation of optimal placement, such as simple assumptions about wind scenarios and regular grid-based arrangements. In a notable study, Martina Fischetti et al. [3] proposed a combination of mathematical optimization and machine learning to estimate the value of the optimized solution. A machine trained with many optimized solutions will investigate whether it can accurately estimate the value of the optimized solution for the new instance. In order to solve the problem of optimizing the layout of an offshore wind farm, which is a specific application, a Mixed Integer Programming model and other cutting-edge optimization techniques are proposed. It can take too much time if you have to evaluate many sites. It was proposed to use machine learning to quickly estimate the potential of the new site. Jagdish Chand Bansal et al. [4] proposed a solution to the wind farm layout optimization problem (WFLOP) using BBO (Biogeography Based Optimization), a new optimization algorithm. This paper recommends the maximum number of turbines as well as ensuring the optimum position of the wind turbines for a given wind farm. In experiments on wind farms of various sizes, BBO has demonstrated superior performance to previous WFLOP solution methodologies. Jonas Schmidt et al. [5] presented results for nine slope-based layout optimization runs of a wind farm with 25 turbines on a flat terrain using three basic wake models and three different inflow scenarios. In all cases, the AEP is maximized, and the constraints are purely geometric. Single flow vectors, uniform wind increases, and realistic synthetic wind increases were studied, and the final layout was compared with a Jensen, Ainslie, and CFD-based numerical wake model. From this, an estimate of the average variation in the turbine position due to different wake models was obtained. Mosetti et al. [6] optimized the placement of turbines to minimize wake losses and maximize energy production by using genetic algorithms (GAs) to simplify square grid-based turbine deployment problems. Yang et al. [7] defined index numbers for each grid and proposed an automatic placement algorithm for turbines using a genetic algorithm such that turbines could be optimally placed in irregular-type wind farms. Elkinton et al. [8,9] established an offshore wind farm layout optimization (OWFLO) framework which minimizes the cost of energy (COE) of wind farms using Park's wake model and an evolutionary algorithm. The OWFLO framework focuses on the development of a wake model, the selection of an appropriate purpose function, and the use of various optimization strategies. The TOPFARM project [10–12] in Denmark included various wake models and operating and maintenance costs to replace CFD interpretation. A multi-fidelity approach was proposed to reduce the design requirements and calculation time, performing optimization by combining sequential linear programming (SLP) and a GA. This paper proposes the development of turbine layout scenarios and a meta-model-based optimization strategy for offshore wind farm layout optimization.

This paper proposes the development of turbine layout scenarios and a metamodel-based optimization strategy for offshore wind farm layout optimization. An EA and PSO algorithm is utilized to solve the optimal wind farm layout problem. The Gori offshore wind farm located in South Korea at the East Sea is selected as the case study to the proposed strategy.

2. Wind Farm Layout Optimization Framework

2.1. Wake Modeling

Wind power efficiency is a function of many variables, such as atmospheric conditions, terrain, wind power turbine design, turbine intervals, and electricity transmission. The wind power turbines used and the wake motion produced by wind power wake dynamics have an immense influence on the productivity and arrangement of wind farm installments. Evaluation of the wake effect of a wind turbine can be divided into numerical and analytic models. The former include the Ainslie (Eddy Viscosity), Reynolds averaged Navier–Stokes (RANS), and farm flow (ECN) models, while the latter include the Jensen, Larsen, and Frandsen Models [13–15]. The wake model employed in this paper is the Jensen (RIS∅/EMD)/Park2 Model for wind farms, in order to calculate wind speed and

power generation losses due to the wake effect of wind turbines. Calculation of the wake effects in wind farms over a long period of time is implemented by the Jensen Model-based Park Model (Park1) of WAsP (Wind Atlas Analysis and Application Program), using the secondary overlay method and combining several wakes using a single wake model. The Park2 Model, proposed by Rathmann, retains a simple representation of the wake, compared to the Park1 Model, but it uses different formulas for the wake reduction by distance and the wake interaction.

The Park1 Model, which can normally be obtained as the wake loss rate with respect to the turbine separation distance, is as follows:

$$\frac{\Delta u_{mn}}{u_{0,m}} = (1 - \frac{u_m}{u_{0,m}}\sqrt{1 - C_T(U_m)})[\frac{D_m}{D_m + 2kx_{mn}}]^2, x_{mn} = x_n + dx - x_m, \qquad (1)$$

where x is the downstream distance, D is the rotor diameter, C_T is the thrust coefficient associated with the incoming wind velocity u, x_{mn} is the downwind horizontal distance between the wind turbines, k is the wake decay constant, and $\sqrt{1 - C_T(U_m)}$ is the normalized rate of inflow of wind turbine m and n, which is modified by the wind speed [15,16].

The calculation of the wake impact area is determined by calculating the cross-area of the wake area caused by the preceding wind turbine and the area of the rotor of the rear wind turbine. The calculated wake impact area is applied to the wake model in proportion to the total area of the rotor, as shown in Equation (2) (and illustrated in Figure 1) in order to calculate the wind speed reduction due to the wake.

$$\frac{\Delta u_{mn}}{u_{0,m}} = (1 - \sqrt{1 - C_T(U_m)})[\frac{D_m}{D_m + 2kx_{mn}}]^2, \frac{A_{overlap,mn}}{A_{rotor,n}}, x_{mn} = x_n + dx - x_m \qquad (2)$$

where $U_{0,m}$ is the inflow wind speed from turbine m and $A_{overlap,mn}$ is the wake area of wind turbine m overlapping with the rotor of wind turbine n. When estimating the combined effect of overlapping wakes, Park2 uses classical perturbation theory, thus assuming that, at some point, the speed-deficit effects from the individual turbines are sufficiently small that they may be simply added. In other words, we apply a linear wake superposition. Park2 Models have been adapted and validated for use in several coast and offshore wind farms. The typical wake reduction coefficient for offshore wind farms (obtained by verification) ranges from 0.045 to 0.075 [15,16].
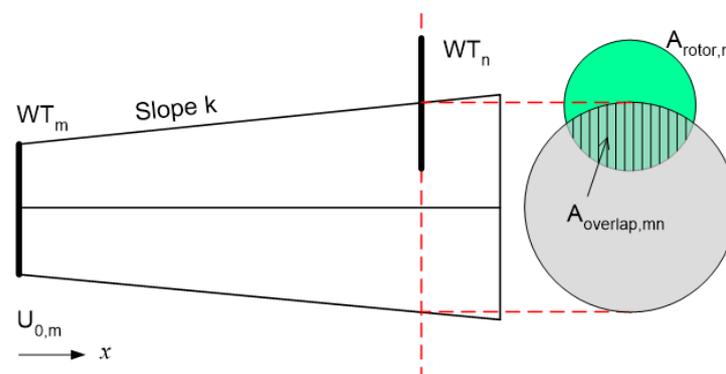

Figure 1. Illustration of the overlapping area used in the Park2 model.

2.2. Optimization Framework

The wind farm layout optimization in this paper focuses on determining the position of N wind turbines when the objective function of wind farm performance is optimally approached. The two main traditional strategies of the turbine array method are to divide the wind farm into a discrete grid in order to explore the optimum grid positions of the turbines or to define the turbine position coordinates as continuous variables, such that all

possible positions within the wind farm can be trialed. Commercial wind farms generally include a large number of turbines (50 and above). If array layouts or grid-based patterns are not assumed for N turbines, the optimization problems can become difficult, involving 2N design variables. In this paper, the turbine arrangement method is composed of the following two scenarios:

(1) Scenario 1: An approach using just patterns in the arrangement of rows and columns of turbines.

(2) Scenario 2: A method of converting a wind farm domain (x, y) into a single parameter or an approach that directly uses the orthogonal coordinates (x, y) of turbines as design variables. In this case, the grid is mapped within the domain and placed by the index number.

The design framework was formalized to model the relationship between the geometry and turbine layout and the energy output in the wind farm. This framework consists of the following main steps:

(STEP 1) Design of experiment (DOE) for turbine layout under scenarios 1 and 2. The DOE data interface process for the two scenarios is as follows.

(STEP 2) Calculation of performance data of wind farm using windPRO for scenarios 1 and 2.

(STEP 3) Store performance data in an ASCII or Excel file (.csv) and convert data into a Binary file to associate with the optiSLang metamodel of optimal prognosis (MOP) function and analyze design sensitivity [17].

(STEP 4) Generate and verify the polynomial and extrapolation-based metamodel.

(STEP 5) Apply evolutionary algorithm (EA) and particle swarm optimization (PSO) to obtain the optimal solution of a multi-objective function using the verified metamodel [18–20].

As the metamodels approximate the computationally intensive functions using simple analytical models (a form of the cheap-to-compute model), it is efficient and simple to perform EA and PSO while reliability is achieved by the metamodels. Figure 2 represents the optimization framework and details the stages of optimizing the placement of wind farms in the case of the Gori offshore area.
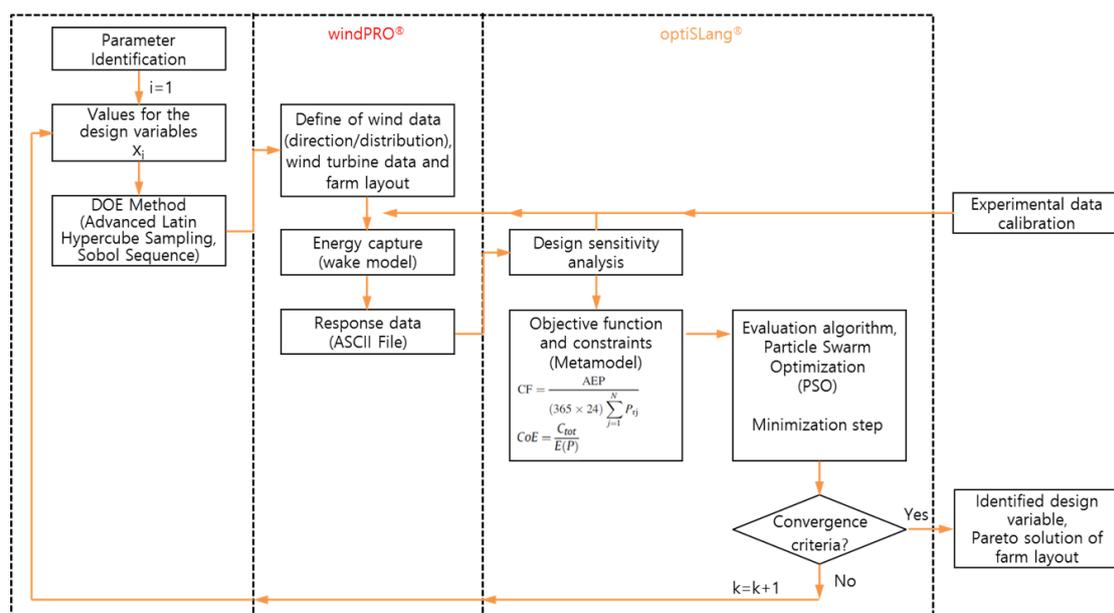

Figure 2. Framework for wind farm layout optimization.

3. Offshore Wind Farm Case Study Results

A feasibility study and efficient design methodology for the offshore wind farm development project on the southeastern coast of Busan were carried out. The Gori sites are located at Easting 526,200 and Northing 3,906,000 (Figure 3). Centralized power supplies of nuclear power and thermal power plants are installed in the vicinity of this area. As such, the use of idle substation equipment and power transmission facilities from the permanently stopped power plants serve to decrease the installation costs of offshore wind power production and to increase their business potential.
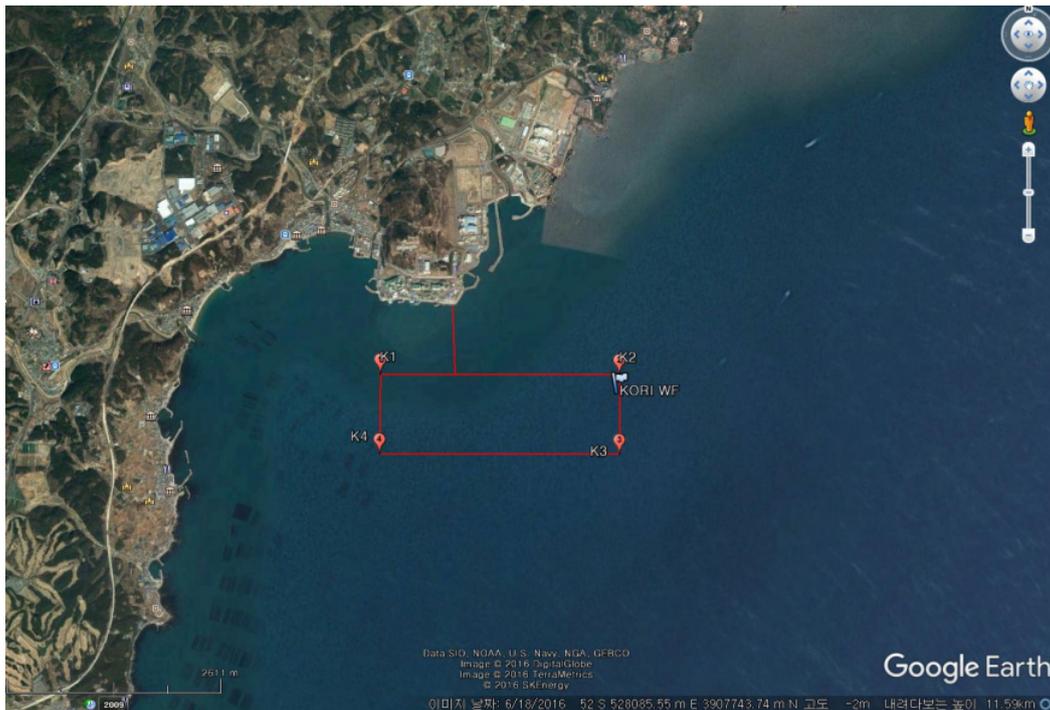

Figure 3. The Gori offshore wind farm location at East Sea of South Korea.

Figure 4 shows the density of wind energy in the area of the intended site of the offshore wind farm using long-term wind speed correction (Measure–Correlative–Predict, MCP) based on the long-term Gori met mast wind data. For a hub height of 110 m, the Weibull parameters (A, K) and the frequency and average wind speed for each direction are summarized, where the main wind direction is NNE. The Weibull distribution parameters are A = 7.14, K = 1.838, and V (mean) = 6.3 m/s.
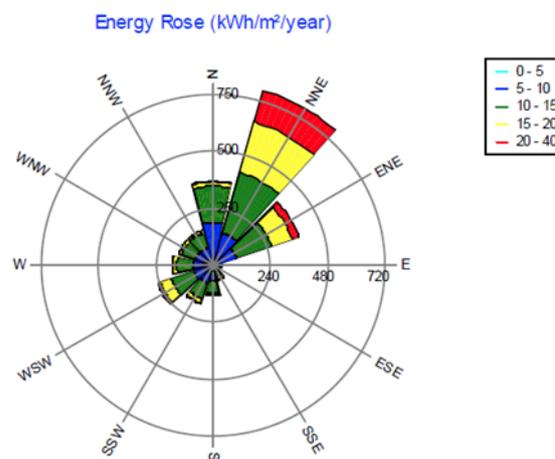

Figure 4. Wind rose diagram at Gori.

3.1. Defining the Design Variable and Objective Function

The purpose of the wind farm layout optimization problem considered in this paper is to maximize the annual energy production (AEP) considering the size and number of turbines at the pre-defined Gori offshore wind farm and to minimize the wake loss. The optimization problem for the layout of the wind farms, considering the design variables x_i and according to the two scenarios, was formulated as follows:

Find WTG1, WTG2, WTG3,$\cdots$, WTG12
Maximize AEP(x_i) or AEP(WTGj)
Minimize Wake Loss(x_i) or Wake Loss(WTGj)
Subject to

$$x^{Lower} \leq x_i \leq x^{Upper} \quad i = 1, 2, \cdots, 9. \ j = 1, 2, \cdots, 12. \tag{3}$$

For scenario 1, Figure 5 represents the nine design variables (x_1–x_9) used for optimizing the wind farm layout. The coastline separation distance, rotation angle in the direction of the main wind direction, lateral angle, and separation distance of the front and rear columns of the turbine were selected. Table 1 presents the design variables and the respective levels. Table 2 shows the experimental arrangement and its interpretation results using the Taguchi mixed orthogonal array with respect to the nine design variables [21].
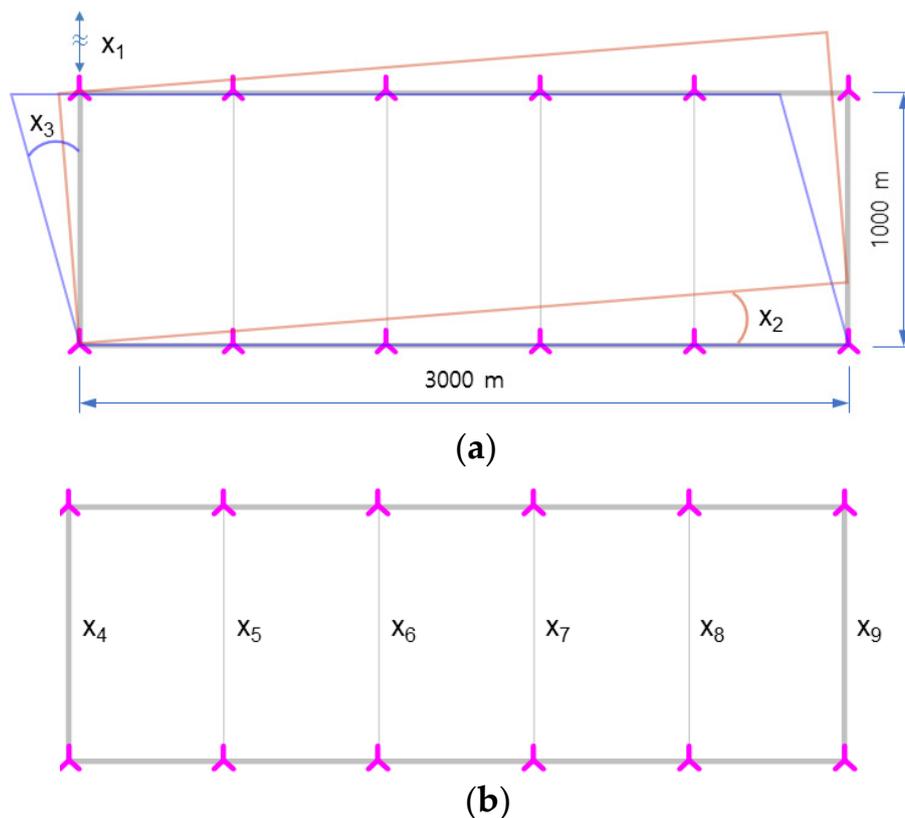
Figure 5. Design variables for offshore wind farm layout based on regular pattern (scenario 1). (**a**) Farm pattern, (**b**) Wind turbine generator column distance.

Table 1. The nine design variables and their levels.

Design Variable	Description	Unit	Initial	Level 1	Level 2	Level 3
x_1	Coastline Distance	m	1000	1000	1250	1500
x_2	Farm Base Angle	Degree	0	−10	0	10
x_3	Farm Side Angle	Degree	90	70	90	110
x_4	1×1 Row Distance	m	1000	556	778	1000
x_5	1×2 Row Distance	m	1000	556	778	1000
x_6	1×3 Row Distance	m	1000	556	778	1000
x_7	1×4 Row Distance	m	1000	556	778	1000
x_8	1×5 Row Distance	m	1000	556	778	1000
x_9	1×6 Row Distance	m	1000	556	778	1000

Table 2. Taguchi orthogonal array L54 matrix and results with respect to the nine design variables.

No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	AEP (MWh/y)	Wake Loss (%)	CF (%)
1	1000	−10	70	556	556	556	556	556	556	167,518.2	9.3	25.8
2	1000	−10	70	556	556	556	778	778	778	168,502.4	8.8	25.9
⋮	⋮									⋮		
54	1500	0	70	778	1000	556	1000	778	556	169,410.6	8.5	26.1

For scenario 2, Figure 6 defines 24 coordinates of each turbine x and y as design variables for the 12 turbines. In the case of scenario 2, the distance between the accumulated turbines was used as a variable. The turbine batch DOE sampling implementation program was configured using Visual Studio 2013 C# on Windows 10.
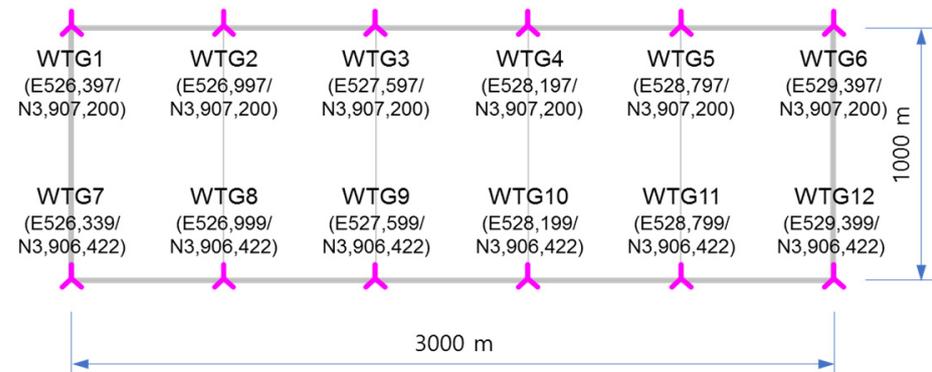
Figure 6. Design variables for offshore wind farm layout based on unrestricted coordinates (scenario 2).

The program was run by entering the turbine interval, site size, number of turbines, output file name, and sampling method in the command window. The results of the program execution were checked in the .csv file, as displayed in Excel.

The intervals for the x and y coordinates of the two accumulated turbines were set to at least 4D of the turbine diameter and defined using the following expression [12,22,23]:

$$\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq 4D. \tag{4}$$

where x_{ij} and y_{ij} are the arrays storing the wind turbine row and column numbers for the wind turbine x and y coordinates for the unrestricted coordinate method. The sum of the distances of all pairs *i* & *j* is a design constraint to minimize the total distance of the accumulated 12 turbine positions.

3.2. Optimal Turbine Layout Results

Optimization of turbine deployment was obtained using total AEP and total wake loss metamodels, as well as EA and PSO. EA and PSO, being a stochastic search algorithm, deals with multiobjective problems significantly better than do gradient based algorithms. It is better exploration abilities, diminished susceptibility to being trapped in local minima, and because it does not suffer from premature convergence. PSO is an algorithm built on the basis of swarm intelligence to solve optimization problems, e.g., search spaces [24], and it has been successfully applied in many areas where optimization problems need to be resolved [25].

Figure 7 shows the convergent process of Pareto optimization by the interaction of turbine layout design variables with EA and PSO, two objective functions AEPs, and the posterior loss. EA and PSO were implemented using the commercial optimal design software optiSLang. EA and PSO sorted the dominance among objects based on non-controlling alignment-based genetic algorithms, which have been widely used in multi-objective optimal design fields, and explore them by emphasizing the best solution direction. EA and PSO populations were both set to 1000 and optimal solutions were obtained after 9884 and 16,051 repetitions, respectively.

(**a**)

Figure 7. *Cont.*

(**b**)
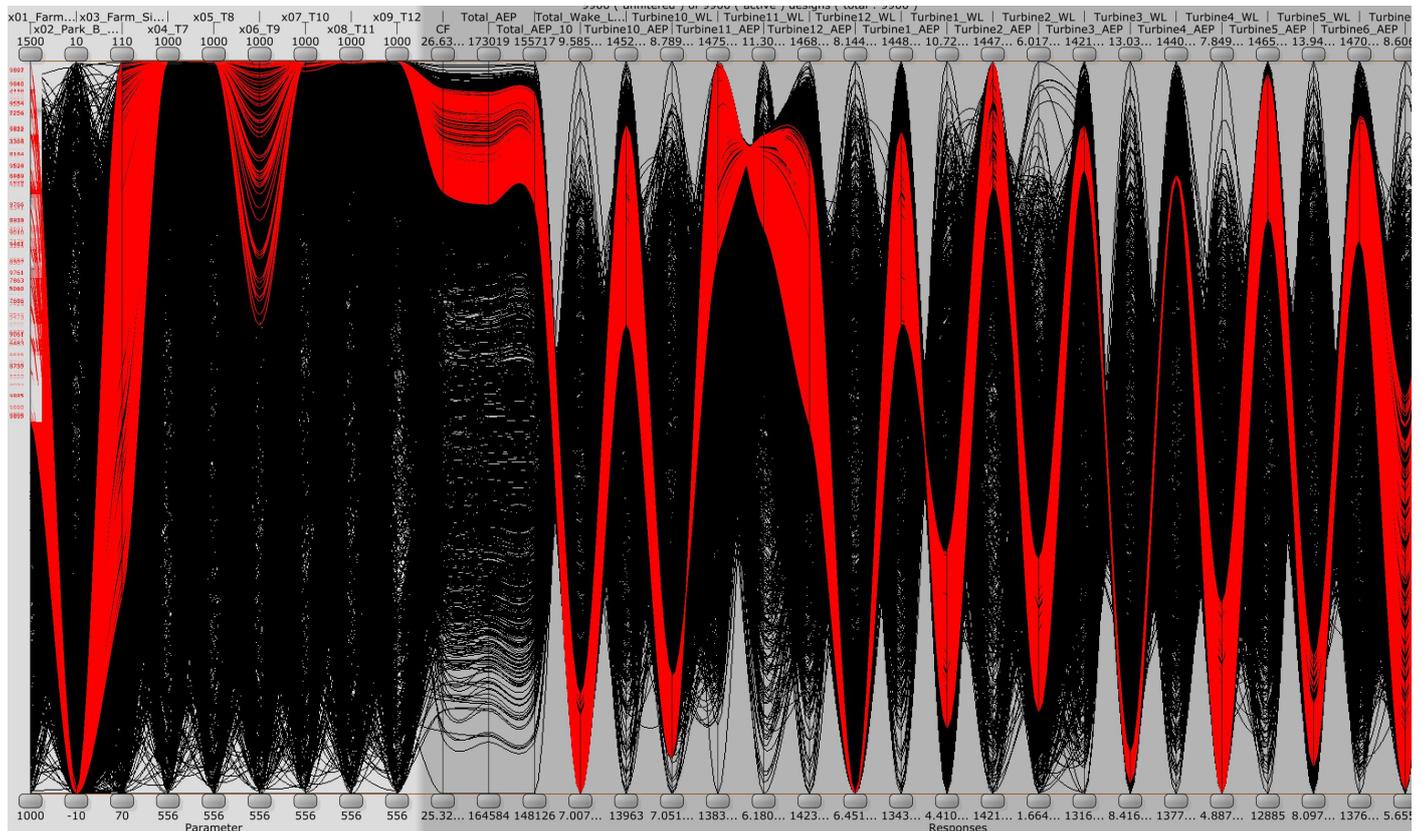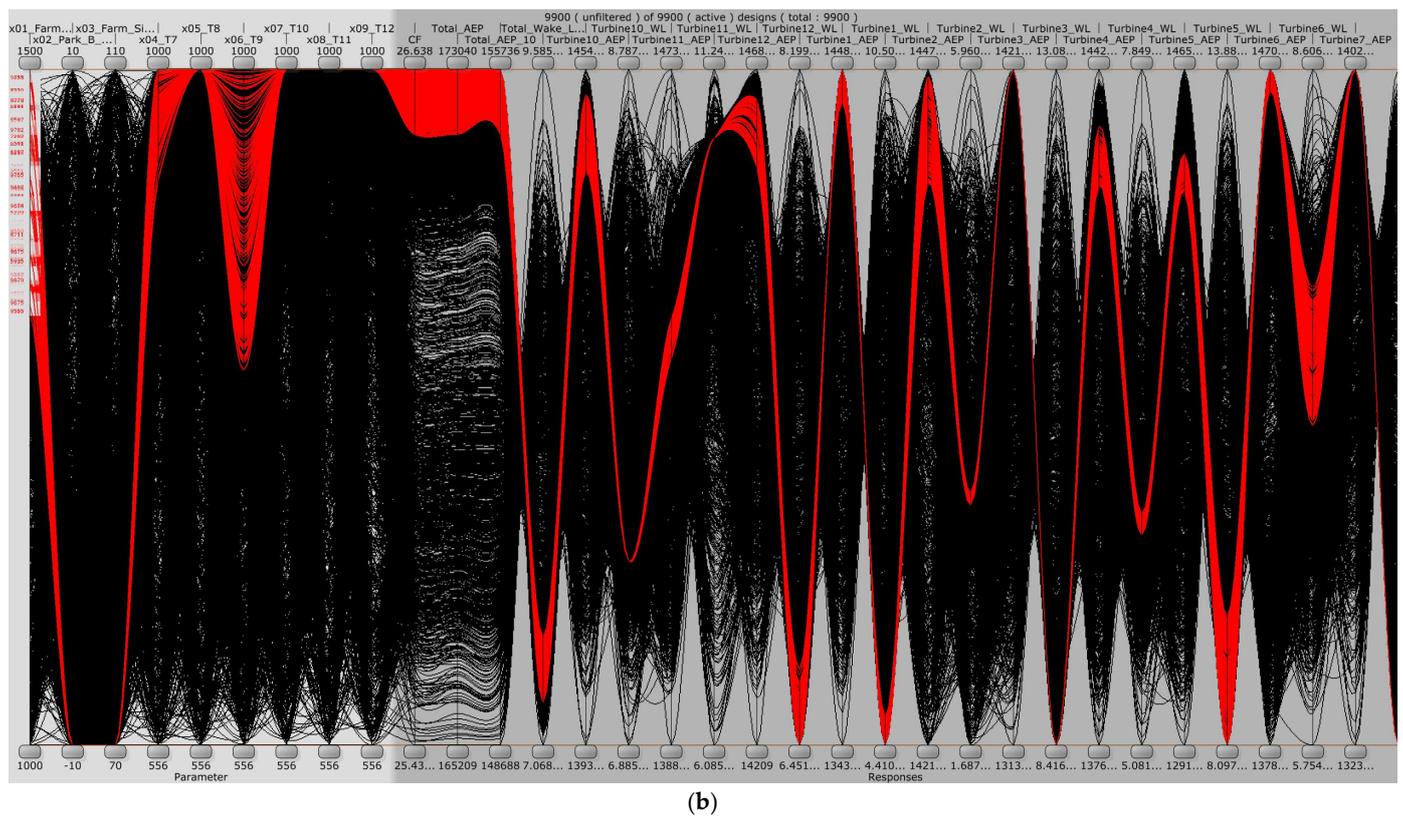
Figure 7. Optimal solutions achieved through (**a**) evolutionary algorithm (EA) and (**b**) particle swarm optimization (PSO) algorithm.

This plot shows all parameter (design variable, AEP, wake loss for objectives, and constraints) for all designs. The failed designs are colored pink, the deactivated are colored gray, incomplete designs are colored violet, and the selected designs are colored red. The optimal solution of EA and PSO shows similar patterns, but EA is better for maximum AEP.

The optimization problem is summarized in Equation (3) and solved using the EA and PSO algorithm. EA and PSO was set to start with a population size of 1000 with an alternative value of 10. The user defined constants involved in EA and PSO are summarized in Table 3.

Table 3. User-defined constants in EA and PSO.

| EA	PSO
Population size: 1000	Population size: 1000
Archive size: 20	Archive size: 20
Crossover probability: 50%	Stop criteria: Diversity < 10%
Mutation rate: 20%	-

Figures 8 and 9 show the results of the optimum turbine arrangement at the Gori offshore wind farm. The wind farm was oriented more in the main wind direction (NNE), compared to the initial turbine arrangement. The spacing between the front and back rows of the turbine was about 7D (Turbine diameter 140 m). Tables 4 and 5 summarize the optimal layout of the wind farm and the optimal locations of each of the 12 turbines, respectively. The optimal solution of EA and PSO shows similar patterns, but EA is better for maximum AEP. With this layout pattern, the annual energy production is 172,437 MWh/y and the capacity factor is 26.5%.
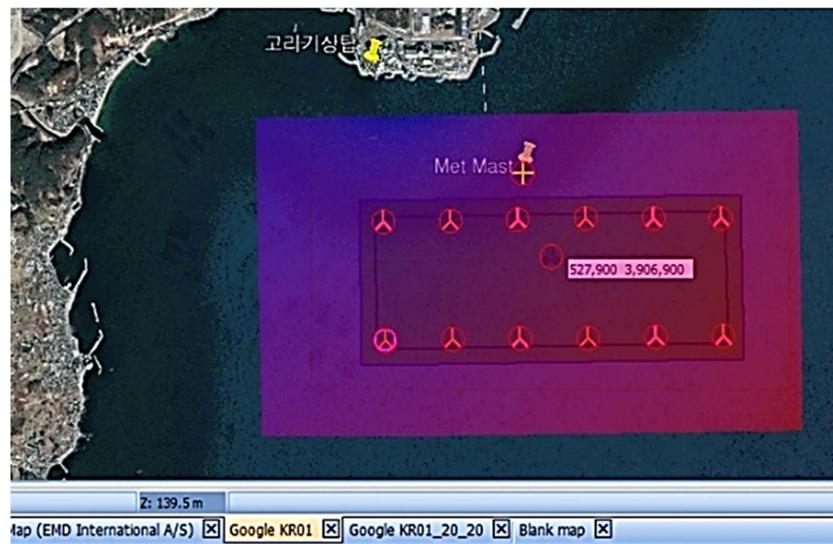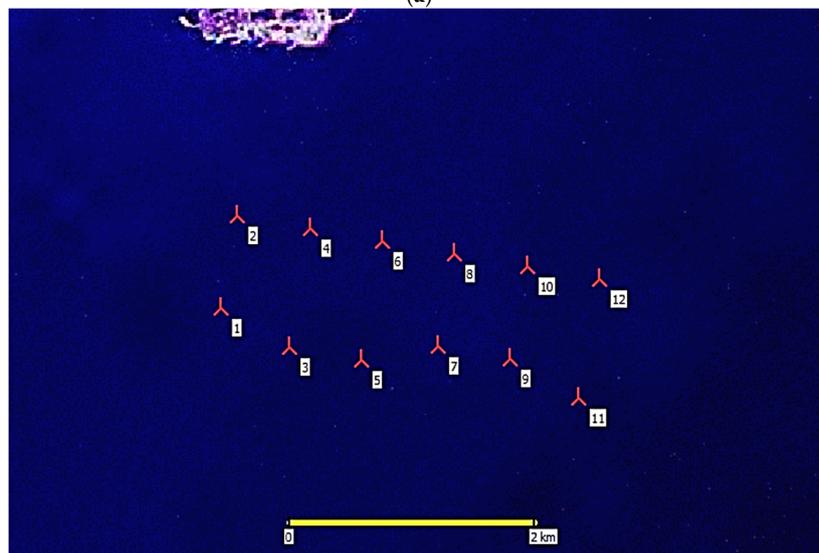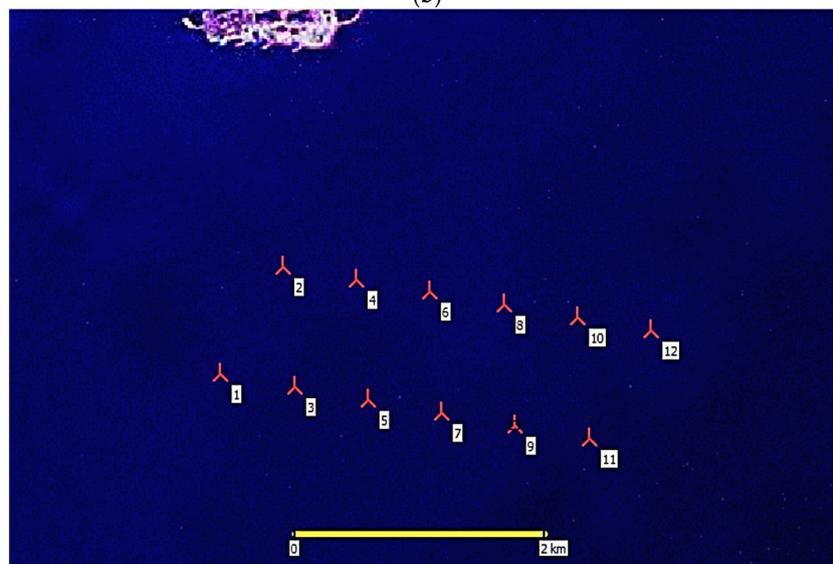
Figure 8. Optimal turbine layout for 12 WTGs (Wind Turbine Generators): (**a**) initial, (**b**) design of experiment (DOE) best solution (**c**) optimal solution.

The wind farm layout results obtained using the proposed optimization framework are shown in Figure 8. Figure 8a shows a designed wind farm that is assumed to have a rectangular shape. Figure 8b shows the turbine arrangement with the maximum AEP at the DOE sample points. The optimum wind farm layout is shown in Figure 8c, and the power generated by each turbine (of this wind farm) is shown in Figure 9. For a given wind increase (Figure 3), the dominant wind direction allows for greater distances between the turbines and the staggered layout pattern in general minimizes the wake losses, thereby increasing the AEP.

The optimal wind farm was oriented more in the main wind direction (NNE) compared to the initial turbine arrangement. The spacing between the front and back rows of the turbine was about 7D (Turbine diameter 140 m). Table 5 summarize the optimal layout of the wind farm and the optimal locations of each of the 12 turbines, respectively. With this optimal layout pattern, the annual energy production is 172,437 MWh/y and the capacity factor is 26.5%. Then, the potential offshore wind power can be estimated as converting 4.6% of electricity consumption in the Busan Metropolitan City region in 2019 in offshore wind farms.
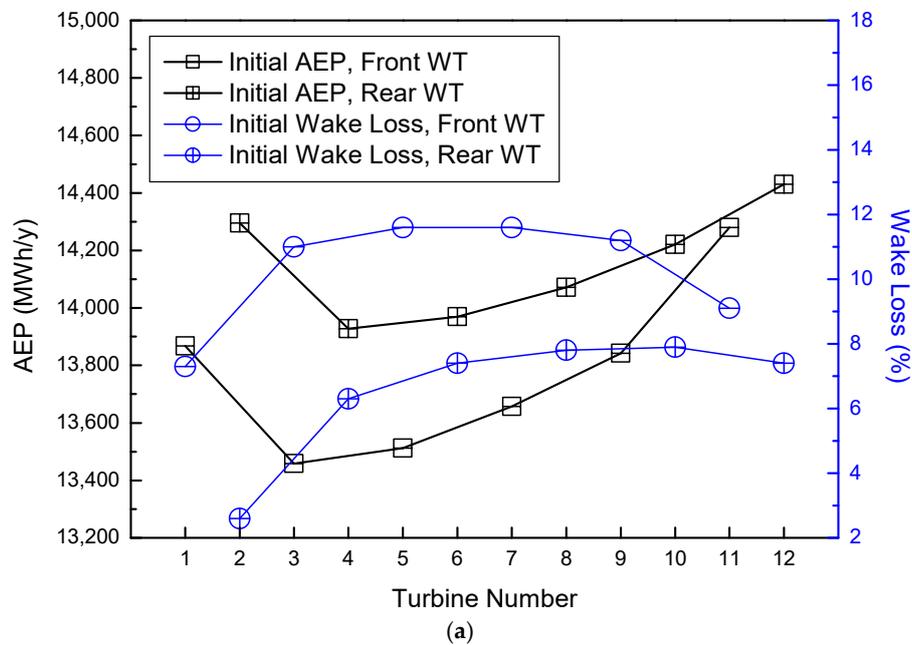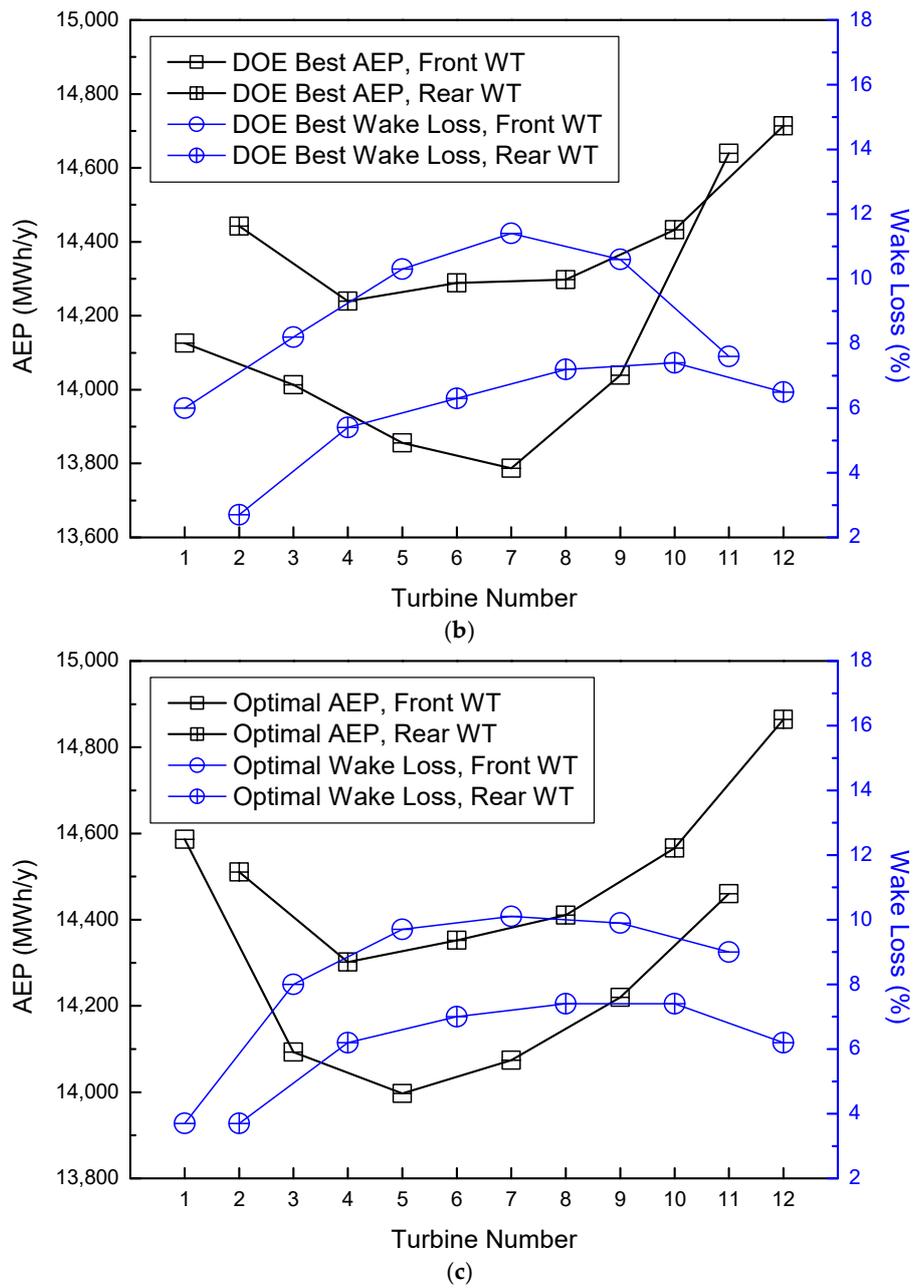

(**a**)

Figure 9. *Cont.*

Figure 9. Optimal turbine layout for 12 WTGs at the Gori wind farm. (**a**) initial, (**b**) DOE best solution (**c**) optimal solution.

Table 4. Key results summarized from the optimization framework.

Solution	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	AEP (MWh/y)	Wake Loss (%)	CF (%)
Initial	1000	0	0	1000	1000	1000	1000	1000	1000	168,000	9.1	25.8
DOE Best	1250	−10	90	778	1000	1000	778	778	1000	170,874	7.5	26.3
PSO	1216.1	−9.2	86.5	1000	988.1	1000	997.9	999.1	997.5	171,762	7.069	26.5
EA	1453.9	−10	70	969.5	999.9	852.1	1000	1000	1000	172,662	7.397	26.5
Reanalysis	1453.9	−10	70	969.5	999.9	852.1	1000	1000	1000	172,437	7.4	26.5

Table 5. Results of calculated annual energy for each of 12 WTGs.

	Results	WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8	WTG9	WTG10	WTG11	WTG12
Initial	Easting (m)	526,339	526,397	526,999	526,997	527,599	527,597	528,199	528,197	528,799	528,797	529,399	529,397
	Northing (m)	3,906,422	3,907,200	3,906,422	3,907,200	3,906,422	3,907,200	3,906,422	3,907,200	3,906,422	3,907,200	3,906,422	3,907,200
	AEP (MWh/y)	13,867.6	14,296.0	13,458.7	13,927.9	13,512.1	13,969.2	13,657.1	14,072.1	13,842.1	14,220.8	14,279.3	14,430.3
	Wake Loss (%)	7.3	2.6	11.0	6.3	11.6	7.4	11.6	7.8	11.2	7.9	9.1	7.4
DOE Best	Easting (m)	526,438	526,571	526,991	527,162	527,582	527,753	528,211	528,344	528,802	528,935	529,354	529,526
	Northing (m)	3,906,169	3,906,935	3,905,846	3,906,831	3,905,742	3,906,727	3,905,856	3,906,623	3,905,752	3,906,518	3,905,429	3,906,414
	AEP (MWh/y)	14,125.5	14,442	14,012.9	14,239.2	13,855.6	14,288.8	13,787.1	14,297.9	14,039.3	14,432.2	14,639.2	14,713.8
	Wake Loss (%)	6	2.7	8.2	5.4	10.3	6.3	11.4	7.2	10.6	7.4	7.6	6.5
Optimal	Easting (m)	526,400	526,899	526,991	527,490	527,582	528,081	528,173	528,671	528,764	529,262	529,354	529,853
	Northing (m)	3,905,700	3,906,567	3,905,596	3,906,462	3,905,492	3,906,358	3,905,387	3,906,254	3,905,283	3,906,150	3,905,179	3,906,046
	AEP (MWh/y)	14,586.6	14,510.9	14,093.0	14,301.6	13,997.1	14,352.6	14,074.0	14,410.6	14,219.8	14,566.1	14,460.3	14,864.6
	Wake Loss (%)	3.7	3.7	8.0	6.2	9.7	7.0	10.1	7.4	9.9	7.4	9.0	6.2

4. Conclusions

This paper has presented a framework to obtain text data by configuring the DOE for optimal turbine placement in the Gori offshore wind farm or to exchange the data needed for optimal design through a low-level programming language. This framework contains a more detailed approach to estimating the AEP of offshore wind farm than existing tools and can be applied to future offshore wind farm development.

(1) For the optimal turbine arrangement at the Gori offshore wind farm, the design variables that most affected the AEP and wake losses were dominant in the x2 complex rotation angle.

(2) In terms of the effect of shoreline clearance, the AEP increased as the shoreline clearance increased, but the wake loss did not linearly reduce as the shoreline clearance increased becoming minimal at 1250 m.

(3) The optimal solution for turbine arrangement was obtained using the AEP, the wake loss metamodel, EA, and PSO and was found to be x_i = [1453.9, -10, 70, 969.5, 999.9, 852.1, 1000, 1000].

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