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A Review of An Optimal Large-Scale Offshore Wind Turbine Farm Layout Techniques

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ABSTRACT

The growth of every nation, be it social or economic development, depends largely on its energy sector. Renewable energy sources such as solar, wind, tidal, geothermal, biogas, etc. are growing significantly faster as an alternative source to conventional sources and are playing a vital role in society. The availability of offshore wind energy will promote substantial growth in wind turbine energy (WTE) for society and strengthen technologies. This paper investigates the use of optimization algorithms for siting wind farm energy (WFE). 6 (six) optimization techniques were reviewed and presented. So, it becomes pertinent to optimally place (WTE) in a large-scale offshore WF by formulating the necessary objective function consisting of wake effect and component costs with WF layout. This study presents a WF model that makes use of the arithmetic optimization algorithm (AOA) techniques to optimally place wind turbines in WFs and compares them to the other techniques.

1. Introduction

Wind farm layout issues can be classified into many optimizations group. Much research work has been carried out in a related area of wind farm layout all focussing and addressing the design of onshore and offshore wind farm layouts. [1 - 4]. This paper present various methods approach analysis adopted in optimization algorithm for the onshore and offshore wind farm arrangement. We further went to consider six basic optimization algorithms for their suitability application for evaluating and analyse the design of wind farm. If a suitable Wind farm land (WFL) is located and considered, the subsequent next step to follow- up now should be wind farm design taking into consideration other factors such as wind farm rating, wind farm size, direction of wind, wake effect, power distribution requirement, etc in to effectively optimize wind farm layout. In Chen *et al.* [5] the authors used the genetic algorithm to optimize different hub heights and WT by maximize the WF. The authors proposed optimizing the wind farm as a two-dimensional area with performance measures such as hub height and wind turbine. Authors in paper Hou et al. [6] developed an optimization technique for placing WTs in a large-scale offshore WF using particle swarm optimization. Also, Bansal & Farswan [7] used the biogeography-based optimization technique to optimally placed the farm layout. The work recycled the Biogeography Based Optimization (BBO) optimization algorithm because it was an unconventional optimization algorithm. Wang et al. [8] presented a WFL optimization by intricate plot partitions. The authors developed optimization model with due consideration to the land owners specification. A design that optimized wind farm layout with a view to obtaining maximum wind energy capture using a constructive approach. The authors employed the use of a mathematical optimization procedure to optimally place WTs on the WF Tifroute & Bouzahir [9]. Paper Ajit et al. [10] proposed employing particle swarm optimization to construct an offshore WFL optimization. Authors expanded default paradigm for WFL optimization by introducing the electrical infrastructure. Double-sided ring topology is commonly functional in accumulator system preparation for large-scale offshore wind farms (OWF), owing to its great dependability against cable errors Zhang et al. [11]. A new approach by assortment of WTs in WFL was developed Gualtieri [12] thereby optimizing the selection procedure. The developed selection method was inspired by the characteristics of the wind turbines that are commercially available. In Wu et al. [13] presented a technique for onshore WFs optimizing layout with a view toward minimizing sound. The authors focused on obtaining the best wind farm architecture in terms of noise, without losing electricity production. Long et al. [14] proposed evolution approach aimed at optimizing WFL. The evolution approach was chosen in order to obtain a low computing cost while preserving performance. An optimization technique for dependable repeated cable arrangements in offshore WFs was developed by Arne & Dag [15], the proposed approach combines two modules which are: a module for path selection and a module for path generation. Reddy [16] WF development schemes entail a full investigation of the adequate land-living. The land-living designated is frequently segmented interested in diverse region, individually possessed via dissimilar property-owners with different land-living estimating. A metamodel and an Evolution Algorithm (EA)/POS Algorithm remained recycled to augment WFL. Authors examined the potential solutions toward the difficult of turbine arrangements in the offshore WF Joongjin et al. **[**17**]**. Kunakote et al. [18] links two research arenas i.e., metaheuristics and WFL design. Proportional presentation of twelve metaheuristics (MHs) on wind farm layout optimisation (WFLO) was steered. We have involved great consideration in current years due to the growing request for substitute energy sources. Assembly the determined amount of energy from WE is directly associated to the layout of WTs in WF Koc [19]. At the end of the review, a wind farm model was formulated and then optimized using AOA optimization algorithm. Comparative analysis of the results obtained was carried out with other optimization algorithms.

1.2 Wind Turbine (WT)

Wind turbines, manufactured in different sizes in either vertical or horizontal axes are used as a scheme that transforms the wind kinetic energy (WKE) into electrical drive Hou et al. [6]. The WT is constituted of fundamental parts such as blades that turn between 13 to 20 rpm, high speed shaft, gearbox, the rotor, generator, low speed shaft, and tower. Typical diagram of a WT is presented in Figure 1. For adequate power to be extracted from a wind turbine, it is pertinent to note that the power being generated is highly dependent on the under listed parameters Feng & Shen [20] and governed by the equation (1):

a. Wind condition
b. The rotor diameter of the wind turbine

$$\mathrm{Pr} = 0.5 C_p \rho G A^3 \tag{1}$$

Where,
Pr : extracted power, ρ : air density, G : rotor swept area and A :upstream wind speed.

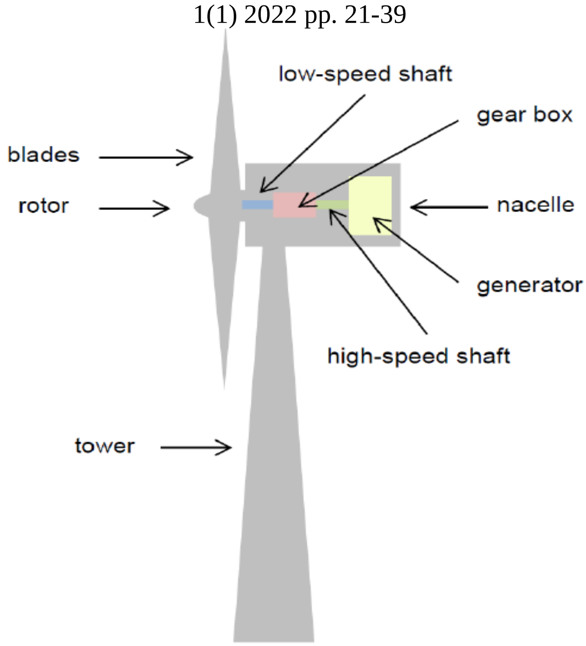

Figure 1: Available Components of a WT Hou et al. [6]

1.3 Types of Wind Turbine

From literatures reviewed, the classification of wind turbines are of two types: Vertical Axis Wind Turbine (VAWT) and Horizontal Axis wind Turbine (HAWT). These categories of the turbines are discussed as follows Pallav & Michaelowa [21]:

a. **VAWT:**

VAWT rotates about a vertical axis. The main advantage of the VAWT is that it doesn't have to face the direction of the wind. At sites with frequent wind changes, such as urban areas, Vertical Axis Wind Turbine could be built. Nonetheless, the Vertical Axis Wind Turbine has high drive costs, low power efficiency, and high dynamic loads on blades as a disadvantage. Figure 2 presents the VAWT.

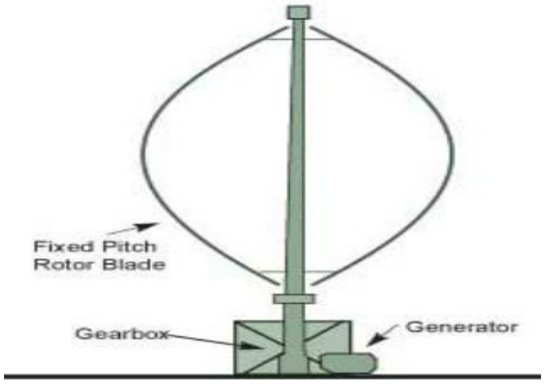

Figure 2: VAWT Pallav & Michaelowa [21]

b. **HAWT:**

The HAWT rotates about a horizontal axis. According to Burton et al. [22], the HAWT is classified as the usefulness near wind control generation because it remains one of the most exclusive choices used. The horizontal axis turbine has two or three rotor blades that are positioned on the opposite of the tower facing the wind, similar to airplane propellers. Downwind turbines were popular in earlier wind energy developments as active mechanisms because there is little certainty that the blades and towers will be in contact with each other. Nonetheless, the tower's turbulence causes frequent loads on the blades and a variance in power Pallav & Michaelowa [21]. The rotor of an upwind turbine is positioned in front of the tower in the direction of the wind so that the tower shadow effect is not taken into account. With a broad range of benefits, 3-bladed upwind turbines are dominant in the wind power generation of utilities. Figure 3 shows the HAWT.

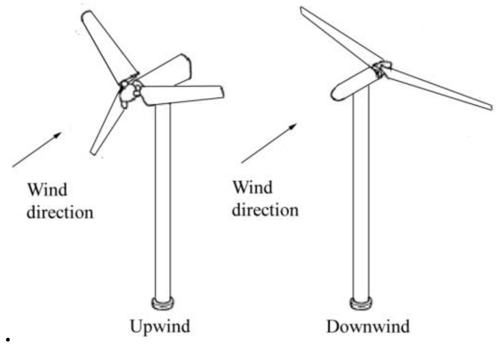

Figure 3: Horizontal Axis Wind Turbine (HAWT)

1.4 Wind Farm Model

WT will always create a wind tracker fashionable the downwind direction and slow down by way of related to the wind received in opposite of the turbine. This expression is termed wake Hou et al. [6]. If the wind speed is less than the evaluated value then the turbines remain only partly associated with the received wind's angle, wake fatalities occur. Most of the earlier designed WFs have malicious wind speeds that remain significantly under the rated value Hou [23]. Other geographical factors depend on the season, the wind directions in the windy moody borderline film, remain naturally unpredictable. With factually documented wind direction and speed distribution data, WFLs are often designed with a view to extracting the highest profit now the greatest collective wind commands. This often consequences now greater streamwise turbine arrangement Hou [23].
WTs absorb dynamism since the wind, and the WT creates a wake downstream thereby reducing wind speed. The wake blowouts by way of the movement progresses downstream, and the wake recuperates towards open flowing settings. Wake effect remains the combined impact continuously the WFE manufacture created by variations in wind speed that are induced through the turbines colliding with individually other Hou et al. [24]. Pertinently, the wake impacts from nearby wind farms as well as the potential influence of future wind must be considered in the design of a wind farm. The wind turbine’s drive train and other tower-top components changes if the wind direction changes thereby aligning the standard trajectory towards the rotor level through the wind route. Wind speed deficit will be influenced by both the fluctuation in wind velocity and the direction of the wind Hou et al. [24]. Figure 4 depicts a wake model with varying speed

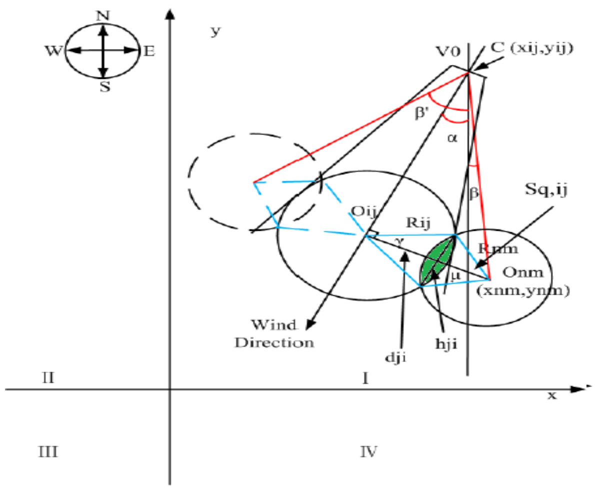

Figure 4: Wake Model with Varying Speed Hou et al. & Kunakote et al. [24, 18]

The intersection of the turbines is needed to be computed in order to predict the velocity deficient that might be experienced by the turbine. The intersection effect is computed using the following equations 2 and 3 Kunakote et al. [18].

$$A_{ij} = R_i^2 \cos^{-1}\left(\frac{c_{ij}^2 + R_i^2 - R_j^2}{2c_{ij}R_i}\right) + R_j^2 \cos^{-1}\left(\frac{C_{ij}^2 + R_j^2 - R_i^2}{2c_{ij}R_j}\right) - \frac{1}{2}\sqrt{(-c_{ij}+R_i+R_j)(c_{ij}-R_i+R_j)(-c_{ij}+R_i-R_j)(c_{ij}+R_i+R_j)} \quad (2)$$

Where;

c_{ij} distance between the centers of both turbines, R_i wake radius of turbine *i* at the same plane turbine *j* and R_j radius of turbine *j*.

The velocity deficit at the *j*-th turbine can then be computed as

$$1 = a\left(\frac{C_0^2}{C(x)^2}\right)\left(\frac{A_{ij}}{A_0}\right) + \frac{V(x)}{V_0} \quad (3)$$

Where; A_0 is the area of the disk of the turbine

The common types of wake models in the literature are discussed as follows:

i. **The Jansen Wake Model**:

According to Jensen, the wakes after the wind turbines were expected towards increase linearly then the wind speed inside the wakes at various statures is considered to remain the equal. The most prevalent wake model used today now in arena of WF optimization is Jansen wake model. This is due to its practicability and simplicity. As such, in this research work, the Jensen wake model will be employed. Three basic wake models are always considered which are the full wake, the no-wake effect, and the partial wake. The graphic shown in Figure 5 is the wind speed deficit. This figure 5 would be used to discuss the wake models.

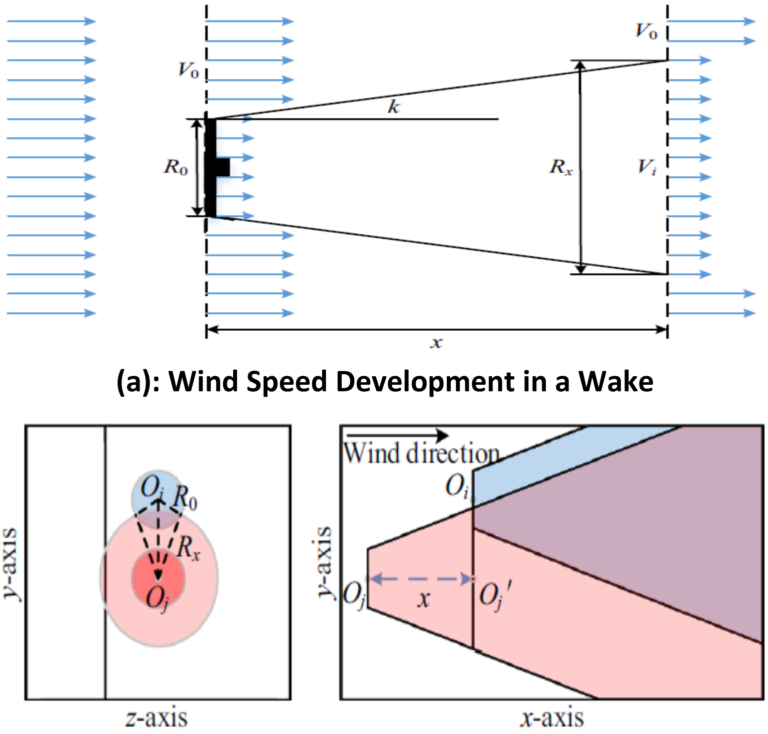

Figure 5: Schematic Representation of the Deficit in Wind Speed Hou et al. [24]

The upstream wind turbine causes a wind speed deficit, which is calculated by determining the area of effective wake influence. The mathematical expression for wind speed deficit is presented in equations (4 & 5) as follows: [6, 24, 18]:

$$T_x = T_0 + kx \tag{4}$$

$$U_i = U_0 - U_0(1-\sqrt{1-C_t})(\frac{T_0}{T_i})^2(\frac{S_{overlap}}{S_0}) \tag{5}$$

Where,

U_i is the speed of the incoming wind, U_0 is wind speed by wake on distance x following the wind flow direction, C_t wind turbine's insertion coefficient, S_0 and $S_{overlap}$ are the rotor swept area and wake swept area respectively, T_x is rotor radius, T_i is circle of the created wake at a distance x after the wind's route and K is wake deterioration persistent.

The suggested rate of k is 0.04 for the offshore atmosphere.

ii. **Larsen Model:**

Larsen developed the semi-analytic wake typical. The model was suggested aimed at resolving wake stocking issue. The Larsen model uses the findings of the full-scale investigate to define the boundary conditions. The following formulas generate for the Larsen Model are presented in equations (6-8) as follows [6, 24]:

$$S_{overlap} = \pi(\frac{35}{2\pi})^{2/5}(3c_1^2)^{2/5}(C_t\pi R_0^2 x)^{2/3} \tag{6}$$

$$U_i = -\frac{U_0}{9}K^2(\pi R^2 C_t x - 2)^{1/3} \tag{7}$$

The expression of the wake area is:

$$K = R_0^{2/3}(3c_1^2 C_t \pi R_0^2 x)^{-1/2} - (\frac{35}{2\pi})^{3/10}(3c_1^2)^{-1/5} \tag{8}$$

where C_1 is an empirically defined constant and K is an intermediate variable.

iii. **Ainslie model:**

Ainslie created a parabolic eddy viscosity model that takes into account wake turbulent mixing as well as ambient turbulence on wake. Because the findings are derived through resolving differential equations, it takes longer towards get the response and is, therefore, superior for wind turbine dynamic analysis.

1.5 Offshore Wind Energy Yields

The computation of energy yields takes into account three factors which are [6] the power output, the duration, and the power losses:

i. **Output power**: calculation of each of the wind turbine's power output using a maximum power point tracking device technique. Thus, total amount of energy produced by wind turbines is expressed as in eqn. (9).

$$P_{prod} = \sum_{j=1}^{N_{col}} \sum_{i=1}^{N_{row}} P_{a,ij} \quad (9)$$

Where,

$P_{a,ij}$ power produced on row i then column j and can be defined as:

$$P_{a,ij} = 0.5\rho C_{p,opt}(\beta'', \lambda_{opt})\pi R^2 u^3 / 10^6 \quad (10)$$

Where,

β'' area angle and λ_{opt} the optimal angle speed ratio for the area angle β', at which the power coefficient resolve to be maximum, u injected wind speed and R rotor circle.

There is a correlation among the wind speed and power output as been presented in the work of Bak et al. [25].

ii. **power losses:** The cable's length is proportional to the distance between the respective wind turbines. As a result, if the wind turbines are spaced widely apart, the energy yields will increase. consequently, the use of longer cables will be necessary. The power loss attached to an AC cable is presented as in eqn. (11) [6]:

$$P_{ll,i} = 3I_i^2 R_{e,i} \quad (11)$$

Where,

I: current of cable i ; $R_{e,i}$: resistance of the cable i

$$R_{e,i} = \rho_{R,i} \frac{l_{R,i}}{S_{R,i}} \quad (12)$$

Where,

$l_{R,i}$: cable length of I, $\rho_{R,i}$ resistivity of the selected cable I; $S_{R,i}$ cable's i sectional area.

Given due consideration towards the power assembly and the power fatalities, the energy yield of a wind farm is computed as in eqn. (13)

$$P_{tol,ll} = \sum_{i=1}^{N} P_{ll,i} \quad (13)$$

This equation (13) defines the total losses within the wind farm. While the equation (14) defines the energy yields of the farm.

$$E_{t,av} = \sum_{t=1}^{T_E} (P_{tol,t} - P_{tol,ll,t})T_t \quad (14)$$

The expressions in the equation are defined as: $P_{ll,i}$ is the power loss of the cable I, $P_{tol,ll,t}$ is the total power loss in interval t, $P_{tol,t}$ is the total power assembly during intermission t, T_E is the period wait for energy yield control

1.6 Review of Pertinent Optimization Algorithms

Optimization as a life tool has become a part of computer-aided design activities due to the fact that it maximizes the efficiency of production. Optimization as a method is done with a view to iteratively comparing multiple solutions until an optimum or satisfactory solution is identified. It takes in a set of inputs and processes them with a view to producing a set of unique outputs as depicted in Figure 6.

Figure 6: Concept of Optimization

In wind energy production, optimization techniques are employed due to some of the following reasons:

i. **Levelized Production Cost**: An offshore wind farm requires a significant investment, with the electrical system accounting for a significant percentage. Maximizing energy production while investing as little as feasible is advantageous.
ii. **Efficiency**: the process of optimizing a wind far improves the general efficiency of the system
iii. **Layout design**: the wind farm layout design is improved using optimization placement techniques

This subsection review some of the different types of optimization algorithms that exist in the literature.

1.7 Particle Swarm Optimization Algorithm (PSO)

Eberhart and Kennedy presented the first variant of PSO in 1995 and since then referred to as the father of PSO Venkata & Babu [26]. The PSO developed was a experiential optimization problem-solving algorithm Roomi & Rajee [27], which was based on the knowledge of the societal behavior of fish schooling, bird flocking, and swarm theory. Five optimization considerations were defined for the algorithm which was Singh & Kaur [28]: candidate solution to a problem, defined as a particle, Velocity which is the rate at which a location change, Fitness: The best answer has been found. PBEST denotes the best value gained in the preceding particle, while GBEST is the greatest means gotten by any unit in the populace.
The swarm is randomly originated through a collection of elements in PSO, and it formerly hunts for optimal conditions by apprising over repetitions. Every repetition, the two best standards are used to apprise each particle. The original is PBEST, which is the best resolution any particle has attained so far, and the second remains GBEST, which is the best resolution followed by any particle throughout entirely groups of the swarm Venkata & Babu [26]. The following equations are used to modernize a particle's velocity and position in relation to the two best values obtained Singh & Kaur [28]:

$$U_i^{t+1} = W^t.U_i^t + A_1.R_1.(Pbest_i^t - y_i^t) + A_2.R_2.(Gbest_i^t - y_i^t) \quad (15)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (16)$$

Where:

y_i^t: position and velocity of the i^{th} particle at time instance t, U_i^t: position and velocity of the i^{th} particle at time instance t, W^t inertial weight at t^{th} instant of time, A_1 & A_2 positive acceleration constant, R_1 & R_2 random values generated in the range [0, 1], sampled from a uniform distribution.
Particle swarm optimization methodology remains set up through the goal of selecting candidates for solutions at random from a search space. The algorithm operates on the obtained fitness values by using the objective function to identify the candidate's solution Blondin [29].

1.8 Artificial Fish Swarm Algorithm

Artificial Fish Swarm algorithm is based on the intellectual behavior of the school of fish. This algorithm operated based on vision and sense whereby fish in the water are said to be more where the most food is located Zhu & Lin [30]. As a result, an AF's environment is primarily the solution space, as well as the state of other AFs. The algorithm functions on the idea that fish have behaviors like preying, swarming, and chasing. These are the behaviors the AFSA imitated. In AFSA, the objective function is expressed as: $y = f(x_i)$, while current nutrition absorption at the position of fish is the objective role. The visible detachment among the artificial fish is $d_{i,j} = \|X_i - X_j\|$, where i arbitrarily created fish and j is also arbitrarily created fish. The maximal dimension of the artificial fish measure is called a step. The behaviors of fish are represented by mathematical expressions that govern how the algorithm functions. These mathematical expressions are discussed as follows:

i. **Preying:** Prey is a fish's basic biological behavior in which the fish senses a place with more food in the water via eyesight or feel and travels fast towards it. If the present state-run of AF is y_i, the artificial fish select a state-run arbitrarily within its graphic space such that Wu et al. [31]:

$$y_j = y_i + rand(0,1) \times visual \quad (17)$$

Where,

y_j new state and y_i previous state

If $f(y_j) < f(y_i)$ or If $f(y_j) > f(y_i)$, then the mathematical expression for these conditions are generated in equations (17) and (18) respectively which are the smallest problematic, it goes onward a phase towards y_j in the directions of the equations.

$$y_i^{(t+1)} = y_i^{(t)} + rand(0,1) \times step \times \frac{y_j^{(t)} - y_i^{(t)}}{\left\| y_j^{(t)} - y_i^{(t)} \right\|} \quad (18)$$

Where,

$\left\| y_j^{(t)} - y_i^{(t)} \right\| = \left| \sqrt{((y_j^{(t)})^2 - (y_i^{(t)})^2)} \right|$: Euclidean space among the artificial fish j and artificial fish i.

$$y_i^{(t+1)} = y_i^{(t)} + rand(0,1) \times step \quad (19)$$

ii. **Swarming:** As a natural method for ensuring their survival and avoiding danger, the fish will congregate and migrate in groups.

Chasing: When a fish discovers food, it will be followed by other fish until they reach the food. Assume that the artificial fish's present state is y_i, and y_m , and stands for the best artificial fish individual within the visible range y_i's . nd is the number of y_m's within visible range. $Y_m = f(X_m)$, if $Y_m < Y_i$ and $nf \times Y_m < \delta \times Y_i$ the artificial fish moves one step towards X_m

1.9. Genetic Algorithm

Genetic Algorithms' theoretical roots were built on a binary string representation of chromosomes and the concept of schema, which is a template that allows for the study of commonalities between chromosomes. This algorithm is dated back to the early 1950s and was first presented by a biologist that made use of computer models to simulate biological systems Moradi & Abedini [32]. In GA, population members are compared to chromosomes, which contain gene sequences. Each structure, which is entirely genotypic in this case, is decoded into a phenotypic expression, which is then assessed using a performance function. Five phases define the genetic algorithm which is: Original populace, Suitability purpose, Collection, Border, and Transformation. The pseudocode that characterized the Genetic Algorithm is presented in Figure 7.

```
Basic Genetic Algorithms
Beginning (1)
    t = 0
    Initialization P(t)
    evaluation P(t)
    While (the stop condition is not verified) do
    Beginning (2)
        t = t + 1
        selection P(t) from P(t-1)
        P(t) ? crossover P(t)
        P(t) ? mutation P(t)
        P(t) ? replacement (P(t-1),P(t))
        evaluation P(t)
    Final(2)
Final(1)
```

Figure 7: Basic Genetic Algorithm Pseudocode systems Moradi & Abedini [32]

1.10 Smell Agent Optimization (SAO) Algorithm

Salawudeen et al. [33] developed and presented the smell agent optimization algorithm in 2019. The developed algorithm is based on smell source. To locate a smell source, the system practices the sensation of smell and an agent's instinctive behind conduct. The sniffing mode and the trailing mode are the two main styles used in the optimization techniques of the created method. The vaporization of aroma molecules from a source is described in the sniffing mode, and the movement of an agent towards the scent molecules is modeled in the trailing mode. The gaseous molecule of scent evaporates from its foundation in the bearing of the agent in the sniffing mode. The agent assesses the concentration of the odor and determines whether or not to follow the direction of the smell molecules. Based on the decision obtained in the sniffing mode, and in the hopes of discovering the molecule's source, the agent intuitively follows (tails) the molecule's journey. The velocity of the smell molecules and how the positions are updated are presented in equations (20) and (21) respectively.

$$U_i^{(t+1)} = U_i^t + r_0 \times \sqrt{\frac{3KT}{n}} \tag{20}$$

Where,

$U_i^{(t+1)}$ is the updated velocity, U_i^t is the current velocity, T is the temperature, n is the mass and K is the Boltzmann constant defined as $1.38 \times 10^{-23} JK^{-1}$

$$y_i^{(t+1)} = y_i^t + [U_i^t + r_0 \times \sqrt{\frac{3KT}{n}}] \tag{21}$$

Where,

$y_i^{(t+1)}$ is: molecule updated position, y_i^t is: previous position of the molecule, r_0 is: a random number.

The trailing mode can be expressed mathematically as follows:

$$y_i^{(t+1)} = y_i^t + r_1 \times olf \times (y_{agent}^t - y_i^t) - r_2 \times olf \times (y_{worst}^t - y_i^t) \tag{22}$$

Where,

r_1 and r_2 are generated randomly at varying intervals, olf is: the olfaction capacity.

1.11 Artificial Bee Colony Optimization Algorithm (ABCOA)

Artificial bee colony (ABC) algorithm stands unique of the swarm-based algorithms best lately familiarized, founded on honey bee's smart fodder behavior Karaboga & Basturk [34]. Social colonies of insects can be seen as a dynamic system for collecting and adjusting the information they obtain from the environment Singh [35]. During the process of information gathering besides change, separate insects do not achieve all the tasks for the reason of their concentrations. But entirely common insect colonies perform according to their partition of labor connected to their morphology. The location of a food basis imitates a possible answer to the optimization problematic in the artificial bee colony algorithm (ABC), and the nectar amount of a diet basis correlates towards the excellence (suitability) of the related answer Akay & Karaboga [36]. The number of employed or observer bees in the population is equal to the number of solutions.

Using the following equation as presented in equations (23) to (24) Karaboga & Basturk [34], food foundation is selected through an artificial observer bee to the probability value related through that food source.

$$D_i = \frac{fin_i}{\sum_{n=1}^{N} fin_n} \tag{23}$$

Where;

fin_i fitness value of I solution, N umber of food sources.

The ABC uses the equation (23) to produce candidate food position

$$U_{ij} = x_{ij} + \partial_{ij}(x_{ij} - x_{ik}) \tag{24}$$

Where,

$k \in \{1,2,\ldots,N\}$ and $j \in \{1,2,\ldots,D\}$ are chosen randomly

∂_{ij}: a random number between [-1 1].

The spy bee notices a new food source which is substituted with x_i as follows:

$$x_i^j = x_{\min}^j + rand(0,1) \times (x_{\max}^j - x_{\min}^j) \tag{25}$$

The performance of individually applicant foundation location is related to that of its preceding one once U_{ij} is created and projected through the artificial bee. If the novel food source has a liquid level that is equivalent to or larger than the ancient unique, it is remembered instead of the ancient unique; otherwise, the ancient unique is remembered.

1.12 Arithmetic Optimization Algorithm (AOA)

The Arithmetic Optimization is a current algorithm that makes use of the distribution conduct of the four elementary mathematics operatives such as Addition (A), Multiplication (M), Division (D), and Subtraction (S) in mathematics. Arithmetic Optimization Algorithm is a mathematically defined and applied optimization method that can be used in a variety of situations of searchable areas Laith et al. [37]. The optimization process in Arithmetic Optimization Algorithm starts with a collection of randomly generated applicant answers (X*), and the best applicant answer in individually reiteration is deemed the best-obtained answer or roughly the optimal so far. Just like other candidate's optimization algorithms, the AOA uses the principle of exploration and exploitation before it starts working. The Math Optimizer Accelerated task is a constant designed and used in the AOA phase such as the exploitation and the exploration. The MOA uses the mathematical expression as:

$$MOA(Iter) = \min + C^* \times (\frac{\max - \min}{m\_iter}) \tag{26}$$

Where;

$MOA(Iter)$ function of the value of the ith iteration,

C^* current iteration and

m_iter maximum number of iterations.

With the introduction of the exploitation phase, the AOA search process commits to the great disseminated standards or judgments (mention to numerous rules) obtained by mathematical calculations using either the Division (D) or Multiplication (M) operators. For the exploration phase, the position updating equation defined in equation (26) was employed.

$$y_{i.j}(C^*+1) = \begin{cases} best(y_j)/(MOP+\epsilon)\times((VB_j - LB_j)\times\mu + LB_j), & r2<0.5 \\ best(y_j)\times MOP\times((VB_j - LB_j)\times\mu + LB_j), & \text{otherwise} \end{cases} \tag{27}$$

Where;

(C^*+1): ith solution in the next iteration,

$y_{i.j}(C^*+1)$: jth position of the ith solution at the current iteration,

$best(y_j)$: jth position in the best-obtained solution so far

ϵ: a small integer number,

μ: a control parameter to adjust the search process and

VB_j and LB_j denotes: upper bound value and lower bound value of the jth position, respectively.

The AOA's exploitation approach is discussed agreeing to the Mathematics operatives, scientific operations involving Subtraction or Addition yielded high-density outcomes, indicating that the manipulation exploration machinery was in use. The mathematical expression for the exploitation is presented as follows:

$$y_{i.j}(C^*+1) = \begin{cases} best(y_j) - MOP\times((VB_j - LB_j)\times\mu + LB_j), & r3<0.5 \\ best(y_j) + MOP\times((VB_j - LB_j)\times\mu + LB_j), & \text{otherwise} \end{cases} \tag{28}$$

Figure 8 present the standard flow chart of the Arithmetic Optimization Algorithm (AOA).

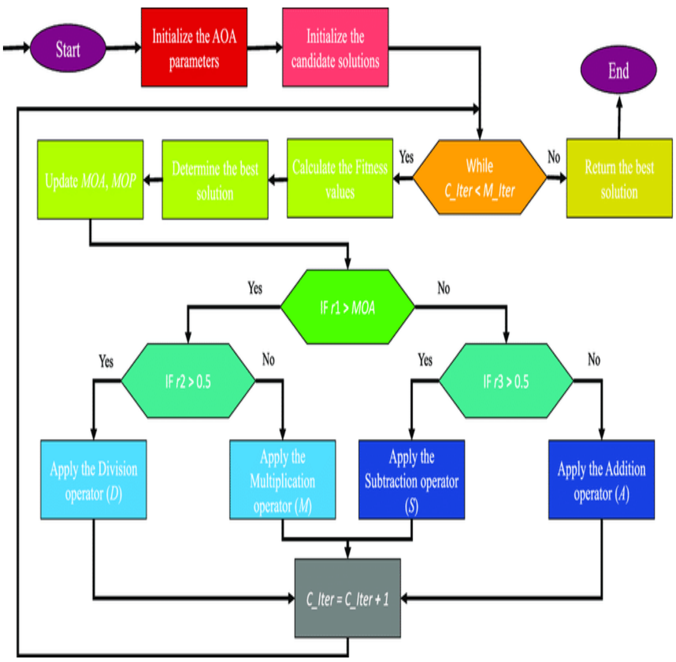

Figure 8: Flow Chart of Arithmetic Optimization Algorithm Laith et al. [37]

Based on the reviewed optimization algorithm, the arithmetic optimization algorithm will be used in this research work due to its simplicity and the fact that it was designed based on the fundamentals of number theory which is an important aspect of modern analysis.

2. Methodology

2.1 Objective Function

The performance of a new wind farm layout design built on existing foundations will be compared to that of a conventional wind farm using the following assessment index: cost of electricity (COE) typically given as [38]:

$$OBJ = \frac{E_{tol,av}}{C_{wt}N_{wt} + C_d N_d} \tag{29}$$

Subject to:

$$x_{\min} \le x_i \le x_{\max}, i \in (1, N_{wt})$$
$$y_{\min} \le y_i \le y_{\max}, i \in (1, N_{wt})$$
$$E_r(x_{i,}y_i) = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2} - d_{\min} \ge 0, \forall i \ne k \tag{30}$$

Where;

C_{wt}, C_d is the cost coefficient of the wind turbine and foundation, $E_{tol,av}$ is the mean energy yield per year.

N_{wt}, N_d is the total number of wind turbine and foundation. $(x_{i,}y_i)$ are the coordinates of the wind turbine.

3. Results and Discussion

3.1 Simulation Result for Applying AOA to the Formulated Wind Farm Model

The comparative results of using the Arithmetic optimization Algorithm (AOA) based on the objectives functions values for all the test scenarios are presented in this subsection. The parameters used for the comparison are the best case, worst case, average and standard deviation as presented in Table 1. Based on the presented result, the scenario II performed better with the AOA as compared to other scenarios. With respect to the standard deviation, the scenario II has the smallest value which implies that the scenario II has a better search consistency in determining the values of the optimal result.

Table 1: Optimization Results of the Objective Function values

Metrics	Scenario I	Scenario II	Scenario III	Scenario IV
Best	0.001416	0.001457	0.001421	0.001461
Average	0.001422	0.001457	0.001423	0.001461
Worst	0.001426	0.00147	0.001426	0.001471
StD	2.97207E-06	4.01194E-06	1.32E-06	2.9731E-06

The comparison of the AOA with other optimization algorithms such as the PSO and WOA are presented in the next subsection.

3.2 Validation via Comparison

This subsection presents the comparative analysis of the algorithm using the mean search convergence and the best search convergence with respect to the AOA, PSO and WOA. The convergence rate and consistency of optimization algorithms are measured using the mean values and standard deviation of objective function values (Mean) as presented in Tables 2 to 5 in this subsection. The performance assessment of the algorithms for test scenario 1 is presented in Table 2.

Table 2: Comparison of AOA with PSO and WOA on Scenario I

Metrics	AOA	PSO	WOA
Best	0.001416	0.001438	0.001413
Average	0.001422	0.001443	0.001429
Worst	0.001426	0.001446	0.001436
StD	2.97207E-06	2.8679E-06	3.77309E-06

Based on the stated result, the WOA iterates the objective function the fewest number of times in order to achieve the best result, whereas the AOA iterates the average amount of times and the PSO iterates the most times to achieve the best result. The PSO has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean search convergence for the scenario I is presented in Figure 9

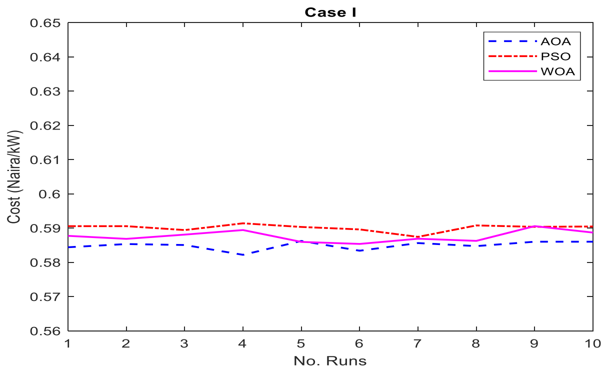

Figure 9: Mean Search Convergence Comparison for the Scenario I

From figure 9, it can be seen that the AOA has the lower mean value which implies that the AOA has the better convergence speed as compared to the WOA and PSO. Figure 10 presents the best search convergence history for the scenario I

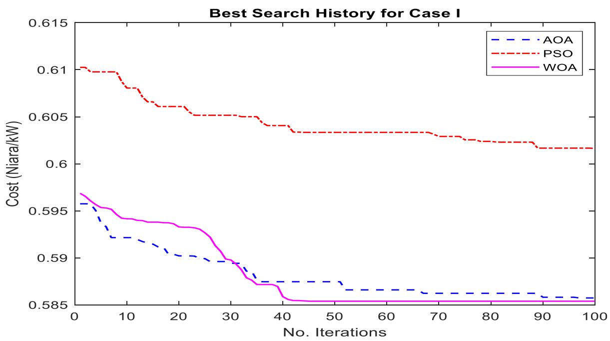

Figure 10: Best Search Convergence Comparison for the Scenario I

From figure 10, it can be seen that the best optimization run for the scenario I is the AOA in comparison to the PSO and WOA.The performance assessment of the algorithms for test scenario II is presented in Table 3.

Table 3: Comparison of AOA with PSO and WOA on Scenario II

Metrics	AOA	PSO	WOA
Best	0.001454	0.00148	0.001467
Average	0.001457	0.00148	0.001475
Worst	0.00147	0.0015	0.001475
StD	4.01194E-06	5.84824E-06	2.44068E-06

Based on the stated result in table 3, the WOA iterates the objective function the fewest number of times in order to achieve the best result, whereas the AOA iterates the average amount of times and the PSO iterates the most times to achieve the best result. The WOA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean search convergence for the scenario II is presented in Figure 11

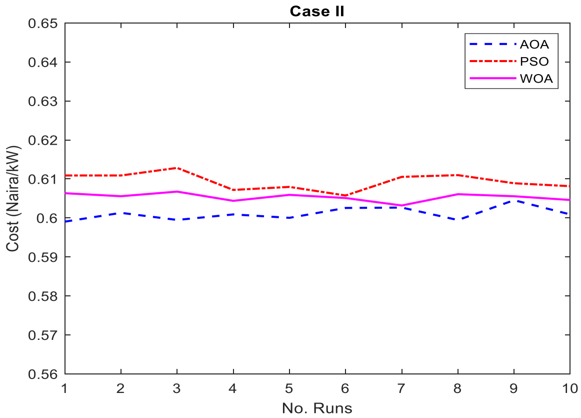

Figure 11: Mean Search Convergence Comparison for the Scenario II

From figure 11, it can be seen that the AOA has the lower mean value which implies that the AOA has the better convergence speed as compared to the WOA and PSO. Figure 12 presents the best search convergence history for the scenario II

Figure 12: Best Search Convergence Comparison for the Scenario II

From Figure 12, it can be seen that the best optimization run for the scenario II is the AOA in comparison to the PSO and WOA.

The performance assessment of the algorithms for test scenario III is presented in Table 4

Table 4: Comparison of AOA with PSO and WOA on Case III

Metrics	AOA	PSO	WOA
Best	0.001421	0.001428	0.001423
Average	0.001423	0.001428	0.001423
Worst	0.001426	0.001436	0.00143
StD	1.32E-06	2.05E-06	1.91E-06

Based on the stated result in table 4, the AOA iterates the objective function the fewest number of times in order to achieve the best result, whereas the WOA iterates the average amount of times and the PSO iterates the most times to achieve the best result. The AOA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean search convergence for the scenario III is presented in Figure 13.

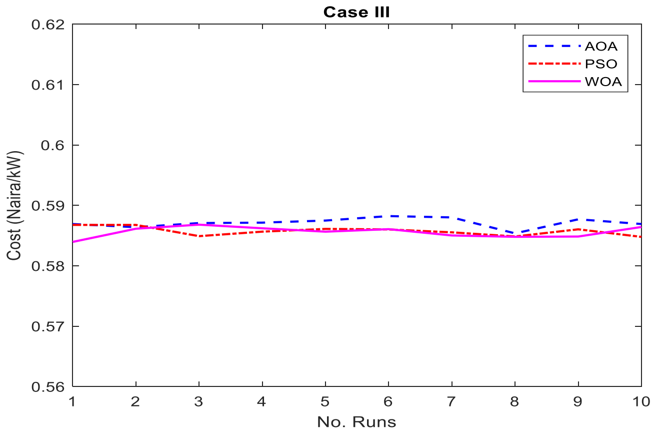

Figure 13: Mean Search Convergence Comparison for the Scenario III

From Figure 13, it can be seen that the WOA has the lower mean value which implies that the WOA has the better convergence speed as compared to the AOA and PSO. Figure 14 presents the best search convergence history for the scenario III

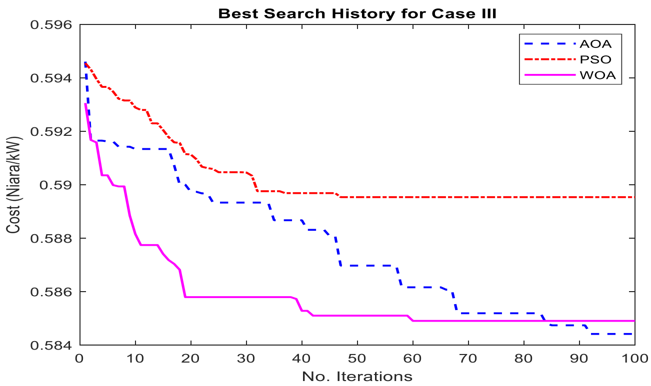

Figure 14: Best Search Convergence Comparison for the Scenario III

From Figure 14, it can be seen that the best optimization run for the scenario III is the WOA in comparison to the PSO and AOA.

The performance assessment of the algorithms for test scenario IV is presented in Table 5

Table 5: Comparison of AOA with PSO and WOA on Case IV

Metrics	AOA	PSO	WOA
Best	0.001461	0.001466	0.001462
Average	0.001461	0.001466	0.001465
Worst	0.001471	0.00147	0.001462
StD	2.9731E-06	1.1211E-06	1.0363E-06

Based on the stated result in table 5, the AOA iterates the objective function the fewest number of times in order to achieve the best result, whereas the WOA iterates the average amount of times and the PSO iterates the most times to achieve the best result. The WOA has the smallest standard deviation, implying that it has a higher search consistency in obtaining the values of the best result. The mean search convergence for the scenario IV is presented in Figure 15

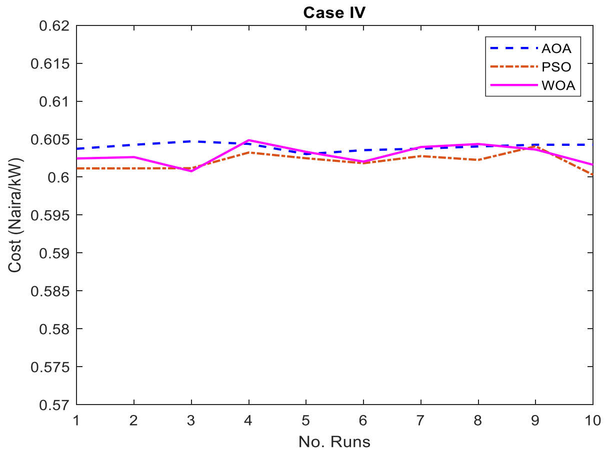

Figure 15: Mean Search Convergence Comparison for the Scenario IV

From Figure 15, it is realized that the PSO has the lower mean value which implies that the PSO has the better convergence speed as compared to the AOA and WOA. Figure 16 presents the best search convergence history for the scenario IV

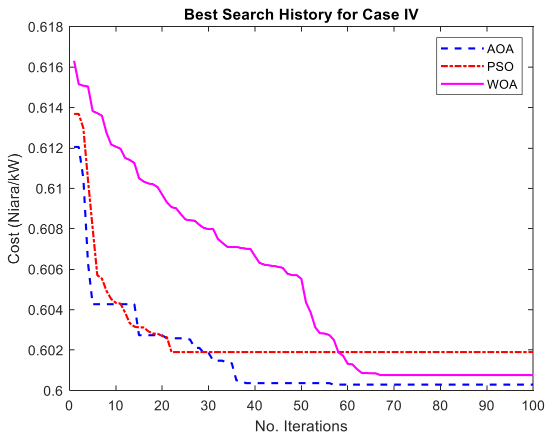

Figure 16: Best Search Convergence Comparison for the Scenario IV

From figure 16, it can be seen that the best optimization run for the scenario IV is the AOA in comparison to the PSO and WOA.

In conclusion, with the presented scenarios, it can be stated that the AOA outperforms the WOA and PSO. The AOA iteration average of time has the highest search consistency in obtaining the values of the best results in scenario I, II and IV. Nonetheless, in Scenario III, the WOA outperforms the AOA and PSO in terms of search consistency in obtaining the values of the best results and has the fewest number of times to iterates for the optimum result.

4.0. Conclusion

Wind Farm Layout optimization (WFLO) should be positions in such a way that the turbines should be attuned easily in that the wind wake effects might be reduced further. Six techniques of optimization were considered and analyses for the utilization of WFLO placement in the off-shore. AOA has been realized, adjusted, and genuine with PSO and the WOA. The amalgamation of any optimization techniques, such as one of those designated in this paper, with properly severe neutral purpose, consumes the skill to enhance offshore WFLs such that the charge of energy will curtailed. The optimal of the positions for the turbines in the FL will be control through the greater budget of the provision buildings and electrical interconnection in profounder water beyond from shore, which overshadowed the superior energy potential farther from shore. This paper offered a technique for assessing the model site and planning of WTs in an offshore WFP. The proposed technique requires combining the AOA with a wind farm model that takes into account the impact of wake on location and placement. The approach was compared to other sister's optimization algorithms such as the PSO and the WOA on the defined wind farm model to assess improvement. In general, the proper optimization will yield a reasonable WFLS.

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