Optimal Layout for Off-shore Wind Farms Using Metaheuristic Search Algorithms

Thoa Thanh Le and Dieu Ngoc Vo

***Abstract*— *This paper proposes some of the recent algorithms, Grey Wolf Optimizer and Whale Optimization Algorithm, for wind farm layout optimization based on maximum wind energy capture. The proposed algorithm is compared with the Particle Swam Optimization algorithm and Optimized module of windPRO software for optimum layout off-shore wind farm and challenging for on-shore wind farm in complex terrain. To evaluate the effectiveness of the algorithms, WAsP software is used to calculate the annual energy production and wake loss of all scenarios. The results showed that the energy yields calculation method proposed in this study with deviations from the WAsP is 3% lower compared to net annual energy production and 3% lower compared to wake loss. In addition, the result of off-shore wind farm layout optimization by this study is better than that of the windPRO 0.1% and on-shore wind farm layout is lower than 1.3% to net annual energy production in comparison. The result proves that the proposed algorithm is able to provide very competitive results. However, the applicability of the proposed algorithm in solving on-shore wind farm layout optimization needs further research and development in the future.*

***Keywords*— Wind farm layout optimization, wind turbine micro-siting, WAsP software, windPRO software, Grey Wolf Optimizer, Whale Optimization Algorithm.**

1. INTRODUCTION

Optimal power flow problems are the important fundamental issues in power system operation. In essence, optimization problems involving minimal generating costs while ensuring reliable operation of the power system. For wind power plant, minimizing generating cost equivalent to maximizing wind energy capture and specifically minimizing wake loss. For achieving this, the optimal micro-siting of wind turbines in wind farms are particularly interested.

Optimal wind farms have been mentioned in several published studies. The problems have been addressed with different objectives, such as, the study of wind behaviour, wake effect analysis, roads access, electrical collector system, foundations, reliability, economic issues, and environmental assessment [1].

Estimated annual energy production (AEP) of a wind farm, the most important model is the analysis of interactions among wind turbines (wake effect). One of the oldest and most widely used wake model was originally developed by N.O. Jensen [2], proposed in 1983, and this model was modified by Katic [3] in 1986.

In 1992, Mosetti et al. [4] applied the wind farm modelling developed by N.O. Jensen for micro-siting wind turbines in wind farms with the objective of maximum energy with the minimum installation cost. That paper square site subdivided into 100 square cells as possible turbine locations in wind farm and optimal wind turbine locations by means of a genetic algorithm (GA). Aytun Ozturk and Norman [5] used the cost model of the wind farm proposed by Mosetti et al., but different realistic objective to maximize profit and the authors proposed a heuristic optimization technique was greedy algorithm. Grady et al. [6] presented work same as Mosetti et al., from objective function and GA. Grady et al. considered some scenarios for optimal wind farm layout and disagreement explanation with the results of previous studies. Marmidis et al. [7] addressed the same economic model proposed by Grady et al., but approaching a statistical and mathematical method so-called “Monte Carlo simulation method”. Şişbot et al. [8] proposed a multi-objective GA for wind farm layout in Gökçeada Island, this study considering the wind speed and direction history and minimized the cost function model. Wan et al. [9] studied objective to maximize AEP and solved by Particle Swam Optimization (PSO). The result demonstrated that the PSO approach was more suitable and effective than that of GA. Kusiak and Song [10] study optimization to maximize AEP as well as to minimize the constraint violation (distance from a wind turbine to each other) by evolutionary strategy algorithm. Saavedra et al. [11] proposed a novel evolutionary algorithm for the wind farm optimization including orography, shape, wind speed, wind direction, cost of installation, connection and internal roads. Firstly, that study used greedy heuristic algorithm to obtain a reasonable initial solution, after that, the heuristic used to seed the initial population of the evolutionary algorithm. Archer et al. [12] developed a wind intensity interface coefficient by wake effect in wind farm. That coefficient then formed part of a mixed integer linear program for wind farm layout optimization. Eroğlu and Seçkiner [13] proposed an ant colony optimization (ACO) algorithm to optimize the same objective function from Kusiak and Song [10]. Wagner et al. [14] maximized the amount of energy by minimization of wake effects. The authors

---

Le Thanh Thoa and Vo Ngoc Dieu (corresponding author) are with Department of Power Systems Engineering, Faculty of Electrical and Electronics Engineering, Hochiminh City University of Technology, Hochiminh City, Vietnam. Tel.: +84 8 3864 7256; E-mail: vndieu@hcmut.edu.vn.

proposed turbine distribution algorithm with specific local search algorithm.

In 2015-2016, some researches related to wind farm layout optimization continue to be published. Jagabondhu et al. [15] proposed a novel 3D micro-siting approach for maximizing AEP, optimal targets including wind turbine position, hub height and rotor radius of each turbine. Arne Klein [16] maximizing AEP applies continuously differentiable and gradient-based solution method, this study modification of the commonly used Jensen wake model. Prateek et al. [17] proposed a novel hybrid optimization methodology for wind farm layout optimization on the number of wind turbines and their location. Huan Long and Zijun Zhang [18] proposed the two-echelon layout-planning model for maximizing AEP. In the first echelon, wind farm models into multiple grid cells and the second echelon, the selected grid cells translate to sets of Cartesian coordinates. The author applied the randomly key genetic algorithm (RKGA) for the first echelon and PSO for the second echelon. Jinkyoo Park and Kincho H. Law [19] maximized AEP using sequential convex programming (SCP), in this study, the first approach uses heuristic search-based optimization algorithms to find a set of good initial solution and the second approach is to parameterize the layout using a small number of design parameters. J. Serrano González et al. [20] proposed the individual selection of operation point of turbine for maximizing AEP, the study applied GA selects optimal pitch angle and tip speed ratio of each individual wind turbine generator. Peng Hou et al. [21] purpose maximizing AEP consider excluding the restricted zones, the paper implemented with the penalty function method applied particle swarm optimization algorithm with multiple adaptive methods (PSO-MAM). Peng Hou et al. [22] study optimized placement of wind turbine in large-scale off-shore wind farm by maximizing the AEP while minimizing the total investment cost, the article applied PSO and the optimization procedure in applicable for wind farm layout with different wind conditions and capacity of wind farm. Zhe Song et al. [23] maximized AEP through micro-siting wind turbines as well as hub height of wind turbines, the model for wind farm layout in 3-dimension (3-d) and sloved objective function by an evolutionary strategy algorithm. A modified PSO approach by Shafiqur Rehman and S. S. A. Ali [24] is proposed for wind farm layout optimization based on cost modeling, which is similar to Mosetti et al. and Grady et al. Rabia Shakoor et al. [25]. A novel method called Definite Point Selection (DPS) is proposed for wind farm layout optimization based on the cost model proposed by Mosetti et al. The author proposes and area rotation method to find the optimum dimension of wind farm shape where maximum area could face the free stream velocity. Jim Y.J. Kuo et al. [26] proposed an algorithm that couples computational fluid dynamics (CFD) with mixed-integer programming (MIP) to wind farm layout on complex terrains, CFD simulations are used to iteratively improve the accuracy of wake deficit predictions while MIP is used for the optimization process.

Currently, there have been several commercial software that efficiently served for the design of wind power plants such as wind resource assessment, wind farm layout optimization, energy yield calculation, electrical collector system, environment, load, economy, operation analyzer. The most popular of these software packages are WAsP [27] and windPRO [28]. The WAsP software suite is the industry-standard for wind resource assessment, siting and energy yield calculation for wind turbines and wind farms. The WAsP software suite is used for sites located in all kinds of terrain all over the world. The wind farm model in WAsP based on a mathematical model of the wake behind a wind turbine, developed by N.O. Jensen [2] and later extended to actual wind farms by Katic et al. [3]. windPRO is a module-based software package suited for project design and planning of both single WTGs and large wind farms which wake effect modeled using the Katic model. The Optimize module of windPRO, optimizes a wind farm layout with regard to maximizing energy production, is widely used and of particular interest. WAsP and windPRO software have been used by design consultants, project developers, wind turbine manufacturers and analytical results from these software easily accepted from investors and project financing support banks.

Meta-heuristic optimization algorithms are becoming more and more popular in engineering applications because they [29]: (i) rely on rather simple concepts and are easy to implement; (ii) do not require gradient information; (iii) can bypass local optima; (iv) can be utilized in a wide range of problems covering different disciplines. Some of the most popular algorithms are [30]: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Evolutionary Programming (EP) and Evolution Strategy (ES). Although these algorithms are able to solve many real and challenging problems, the so-called No Free Lunch theorem [31] allows researchers to propose new algorithms. According to this theorem, all algorithms perform equal when solving all optimization problems. Therefore, one algorithm can be very effective in solving one set of problems but ineffective on a different set of problems. This is the foundation of many works in this field. Some of new algorithms by Seyedali Mirjalili et al. such as [32], Whale Optimization Algorithm (WOA), Sine Cosine Algorithm (SCA), Moth-Flame Optimization algorithm (MFO), Dragonfly Algorithm (DA), Multi-Verse Optimizer (MVO), Ant Lion Optimizer (ALO) and Grey Wolf Optimizer (GWO), Robust Optimization (RO), have proved that they are very competitive compared to the state-of-art meta-heuristic algorithms as well as conventional methods.

This article proposes to apply Grey Wolf Optimizer (GWO), the second most cited paper of the ADES journal [32], and Whale Optimization Algorithm (WOA), a new optimization technique for solving optimization problems in 2016, for wind turbine micro-siting in wind farm purpose obtained the maximum annual energy production. The proposed algorithm is compared with the most popular algorithms PSO and wind farm layout optimization from module Optimize of windPRO. All optimized algorithm to the same input data (the actual orographic contour map, roughness map and wind resource data), AEP of all scenarios have been calculated and analyzed by the WAsP, to objectively evaluate all proposed algorithms.

This article considered optimal micro-siting wind turbine in a rectangular boundary and irregular boundary of wind farm, arranged for off-shore wind farms. In addition, the article challenge micro-siting wind turbine on-shore wind farm in complex terrain for further research and development in the future.

2. PROBLEM FORMULATION

2.1 Assumptions

This article acknowledges the following assumptions:

Assumption 1: The wind turbines in wind farm are identical.

Assumption 2: The *capacity* of wind farm (the number of wind turbines) is given and fixed.

Assumption 3: The wind turbine location is characterized by its two dimensional Cartesian coordinates (x, y). It means that the surface roughness of wind farm terrain is slightly changeable. The planning solution is represented by a set of coordinates $(x_i, y_i), i = 1, \cdots, N$.

Assumption 4: The wind speed v conditioned on wind direction θ in the wind farm follows a Weibull distribution presented as [33]:

$$p(v, c, k) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left(-\left(\frac{v}{c}\right)^{k}\right), c = c(\theta), k = k(\theta) \quad (1)$$

where $p(\cdot)$ is the Weibull probability density function, c is the scale parameter, and k is the shape parameter.

Assumption 5: All wind turbines' rotors are positioned perpendicular to the wind direction θ.

2.2 Wake modeling

Wind turbine's wake effect, a distinct division can be made into the near and far wake region. In which, the near wake is the affected area just behind the turbine rotor and the far wake is the affected area beyond the near wake. In wind farm layout optimization based on AEP, the far wake becomes more important than near wake [34] because wake effect to lower velocity and higher turbulence intensity. The wake effect is one of the main causes to reduce the output of wind farms, therefore, the maximum AEP based on Minimum wake effect has been stated from several studies. Fig. 1. is the real wake effect and Fig. 2. is the velocity profile behind wind turbine including near wake and far wake.

One of the oldest and most widely used wake model developed by N.O. Jensen [2] was modified by Katic in [3]. That model is quite simple and the authors assume that a linearly expanding wake effect behind wind turbine depends on the distance between the turbines downwind. This effect makes the wind speed behind the turbine weaker against original wind speed, illustrated in Fig. 3.

Fig. 1. The real wake effect [23]

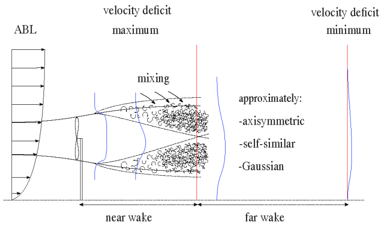


Fig. 2. The velocity profile behind wind turbine [34]

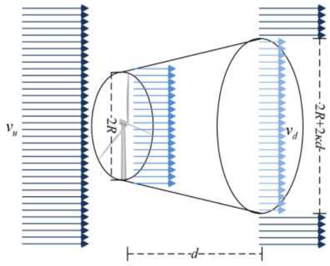


Fig. 3. The approximated wake effect [23]

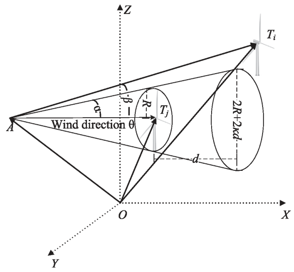


Fig. 4. The wind turbine locations and the wake [23]

The velocity deficit of the wake at a given position d is [10]:

$$V_{def} = 1 - \frac{V_{down}}{V_{up}} = \frac{1 - \sqrt{1 - C_t}}{(1 + \kappa d/R)^2} \quad (2)$$

where C_t is the thrust coefficient of the turbine, κ is the wake spreading constant (the constant has a default value of 0.075 for on-shore wind farm and value of 0.04 for off-shore wind farm in most cases [27]), and d is the distance behind the upstream turbine following the wind direction θ. Distance from wind turbine $i(x_i, y_i)$ and wind turbine $j(x_j, y_j)$ is [10]:

$$d_{i,j} = \left|(x_i - x_j)\cos\theta + (y_i - y_j)\sin\theta\right| \quad (3)$$

When a turbine is affected by the wakes of multiple, the velocity in the (fully developed) wake is given by Eq. (4) [10]:

$$V_{def_i} = \sqrt{\sum_{j=1, j\neq i, \beta_{i,j}<\alpha}^{N} \left[\frac{1 - \sqrt{1 - C_t}}{\left(1 + \kappa d_{i,j}/R\right)^2}\right]^2} \quad (4)$$

where parameter $\alpha (0 \le \alpha \le \pi/2)$ is calculated as arctan (κ) and the angle $\beta_{i,j}, 0 \le \beta \le \pi$, between the vector from imaginary cone vertex to turbine i and turbine j as given in Fig. 4., is calculated as [10]:

$$\beta_{i,j} = \cos^{-1}\left\{\frac{(x_i - x_j)\cos\theta + (y_i - y_j)\sin\theta + R/\kappa}{\sqrt{\left(x_i - x_j + \frac{R}{\kappa}\cos\theta\right)^2 + \left(y_i - y_j + \frac{R}{\kappa}\sin\theta\right)^2}}\right\} \quad (5)$$

And [10] also demonstrated that wind turbine j is in the wake of turbine i if turbine j in the imaginary cone.

Since only the scale parameter c of the Weibull distribution is affected by the wake effect, the wake loss reflected in the statistical distribution level is expressed as [10]

$$c'(\theta) = c(\theta).(1 - V_{def}) \tag{6}$$

2.3 Power curve modeling

Wind turbine manufacturer supplies power curve of wind turbine and it is guaranteed to wind turbine operator. Accurate power curve model help accurately predict the power output produced by the turbine as well as AEP of wind farm.

Polynomial model using fitting toolbox is introduced by Mohan Raj et al. [35], the data, power output from wind turbine, was fitted for 4th, 7th and 9th degree polynomial and 9th degree polynomial is observed to be best fit.

The expression used for 9th degree polynomial is as follows:

$$f(x) = p_1x^9 + p_2x^8 + p_3x^7 + p_4x^6 + p_5x^5 + p_6x^4 + p_7x^3 + p_8x^2 + p_9x + p_{10} \tag{7}$$

Fig. 5 and Fig. 6 show the comparative performances of polynomial model and the actual power output of this study. It is observable that the proposed model curve is closer to the actual power output curve.

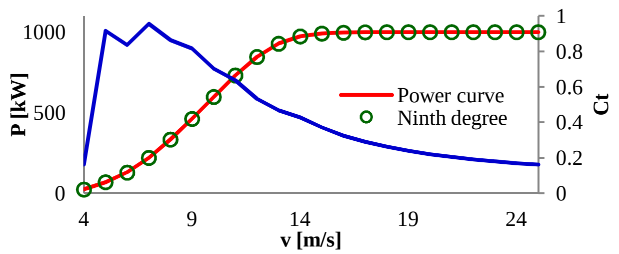


Fig. 5. 1MW WAsP sample wind turbine power curve.

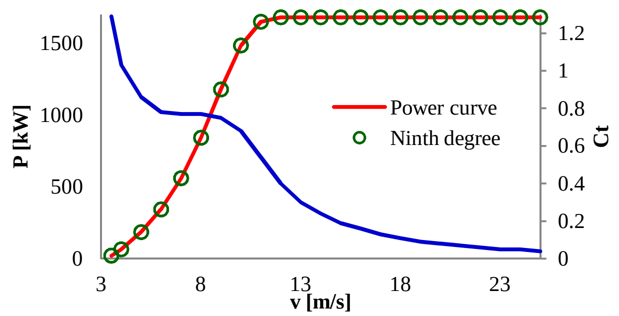


Fig. 6. GE 1.68-82.5 wind turbine power curve.

Therefore, power curve of wind turbine can be written as:

$$f(v) = \begin{cases} 0, & v_i < v_{cut\ in}, v_i > v_{cut\ out} \\ f(x)\ in\ Eq.(7), & v_{cut\ in} \le v_i < v_{rated} \\ P_{rated}, & v_{rated} \le v_i \le v_{cut\ out} \end{cases} \tag{8}$$

Along with the power curve, the thrust coefficient is another important dimensionless number in wind turbine aerodynamics to calculate wind farm wake effects and wind farm efficiency. This value can be found from wind turbine manufacturer or library of WAsP and windPRO.

2.4 Energy production modeling

2.4.1 Behavioral model of the wind

The statistical behavior of wind is typically modeled by two parameters, wind direction and wind speed. They are visual depictions in wind rose and wind speed distribution curve. In which, wind rose describes the wind direction and the probability of occurrence for each of the sectors while the wind speed distribution curve describes wind speed characterized as a Weibull distribution, as shown in Eq. (1)

2.4.2 Average power produced

The average power output from a wind turbine is the power produced at each wind speed times the fraction of the time that wind speed is experienced, integrated over all possible wind speeds. In integral form, this is [33]:

$$E(P,\theta) = \int_0^\infty f(v)p(v,c(\theta),k(\theta))dv \tag{9}$$

where $p(v,c,k)$ is a probability density function of wind speed, as given in Eq. (1) and $f(v)$ is power curve as given in Eq. (8).

Integrating the expression in (8) for θ in the range 0–360 provides the expected energy production of a single wind turbine [18]:

$$E(P) = \int_0^{360} p_\theta(\theta)d\theta \int_0^\infty f(v)p(v,c(\theta),k(\theta))dv \tag{10}$$

2.4.3 Numerical Integration of Wind Power produced

Wind direction is divided into h intervals, $0^o \le \theta_1 \le \theta_2 \le \cdots \le \theta_{h-1} < 360^o, \theta_0 = 0^o, \theta_h = 360^o,$. Each interval is associated with a relative frequency $0 \le f_i(\theta) \le 1$, which is the probability that the wind direction belongs to the ith interval.

To estimate the expected power output of a wind turbine, a numerical integration approach is applied. By discretizing the wind direction into h intervals of equal width, the wind power output conditioned on direction θ is integrated according to [18]:

$$E(P) = \sum_{i=1}^{h} f_i(\theta) \int_0^\infty f(v) \frac{k_i(\theta)}{c_i'(\theta)} \left(\frac{v}{c_i'(\theta)}\right)^{k_i(\theta)-1} e^{-\left(\frac{v}{c_i'(\theta)}\right)^{k_i(\theta)}} dv \tag{11}$$

Wind turbine starts generating electricity in wind speed range of cut-in and cut-out of power curve. Therefore, integral of $(0,\infty)$ of Eq. (11) can be calculated in $(v_{cut\ in}, v_{cut\ out})$.

Once the wind speed and wind direction are discretized into intervals, $c_i(\cdot)$ and $k_i(\cdot)$ in (16) can be estimated from the historical wind data. From Eq. (11) can be calculated AEP of wind farm.

2.4.4 Objective functions

This paper consider the optimization wind farm layout by maximizing the wind energy capture $Obj = \max\,[\Sigma E(P)]$

3. SOLUTION ALGORITHM

This paper proposed applying some recent Meta-heuristic algorithms for wind farm layout optimization:

- Particle Swam Optimization (PSO): the most popular algorithm.
- Grey Wolf Optimizer (GWO): the second most cited paper of the ADES journal.
- Whale Optimization Algorithm (WOA): a new optimization technique for solving optimization problems in 2016.

The wind farm layout result is compared with optimal layout using windPRO software (module Optimize) to the same input data. to objectively evaluate the proposed algorithm, the entire calculation results will be calculated and analyzed by WAsP software.

3.1 PSO algorithm

PSO [36] is a population-based and stochastic optimization algorithm. It was stylized representation of the movement of organisms in a bird flock or fish school, and developed by Kennedy and Eberhart.

The PSO algorithm starts with a population of particles whose position matrix $Z = \left[z_1^T \cdots z_i^T \cdots z_{N_p}^T\right]^T$ and velocity matrix $V = \left[v_1^T \cdots v_i^T \cdots v_{N_p}^T\right]^T$ are randomly initialized in the search space. N_p represents the population size. $z_i = \left[z_{i,1} \cdots z_{i,j} \cdots z_{i,n}\right]$ and $v_i = \left[v_{i,1} \cdots v_{i,j} \cdots v_{i,n}\right]$ represent the position and velocity vectors of the ith particle, respectively. n represents the number of decision variables.

The search for the optimal position is carried out by biasing the population toward both their own historical best positions Z^p and the swarm's historical best position z^g.

Elements of the velocity and position matrices are updated [9]

$$v_{i,j}(t+1) = \chi\Big(v_{i,j}(t) + c_1 r_1\left(z_{i,j}^p(t) - z_{i,j}(t)\right) + c_2 r_2\left(z_j^g(t) - z_{i,j}(t)\right)\Big) \quad (12)$$

$$v_{i,j}(t+1) = \chi\Big(v_{i,j}(t) + c_1 r_1\left(z_{i,j}^p(t) - z_{i,j}(t)\right) + c_2 r_2\left(z_j^g(t) - z_{i,j}(t)\right)\Big) \quad (13)$$

$$v_{i,j}(t+1) = \begin{cases} -v_{max,j}, v_{i,j}(t+1) < -v_{max,j} \\ v_{max,j}, v_{i,j}(t+1) > v_{max,j} \\ v_{i,j}(t+1), otherwise \end{cases} \quad (14)$$

$$z_{i,j}(t+1) = z_{i,j}(t) + v_{i,j}(t+1) \quad (15)$$

$$z_{i,j}(t+1) = \begin{cases} z_{min,j}, z_{i,j}(t+1) < z_{min,j} \\ z_{max,j}, z_{i,j}(t+1) > z_{max,j} \\ z_{i,j}(t+1), otherwise \end{cases} \quad (16)$$

where $i \in \{1, \cdots, N_p\}$ is the particle index, $j \in \{1, \cdots, n\}$ is the dimension index, $t \in \{1, \cdots, T_{max}\}$ is the interation index, T_{max} is the maximum number of interations, χ is the constriction factor $(\chi = 2/|2 - c - \sqrt{(c^2 - 4c)}|$, c=c1+c2,c>*4*. c1 and c2 are positive constants referred to as the cognitive and the social parameters, respectively. r_1 and r_2 are random numbers uniformly distributed in the range [0,1]. $z_{min} = \left[z_{min,1} \cdots z_{min,j} \cdots z_{min,n}\right]$ and $z_{max} = \left[z_{max,1} \cdots z_{max,j} \cdots z_{max,n}\right]$ are lower and upper bounds of the position , respectively. $v_{max} = \left[v_{max,1} \cdots v_{max,j} \cdots v_{max,n}\right]$ is the maximum velocity and usully set to $z_{max} - z_{min}$.

3.2 GWO algorithm

Grey Wolf Optimizer (GWO) [30] inspired predatory behavior of the gray wolf. The three main steps of hunting, searching for prey, encircling prey, and attacking prey. The GWO considers alpha (α), beta (β), delta (δ) and omega (ω) are employed for simulating the leadership hierarchy and that is the sequence of the best of fitness solutions.

3.2.1 Encircling prey

Mathematically model encircling behavior the following equations

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \quad (17)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \quad (18)$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf.

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (19)$$

$$\vec{C} = 2.\vec{r}_2 \quad (20)$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0,1].

3.2.2 Hunting

The best candidate solution (anpha, beta, delta and omegas) will be saved and updated.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \quad (21)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \quad (22)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (23)$$

3.2.3 Attacking prey (exploitation)

The vector $\vec{A}$ is a random value in the interval $[-2a, 2a]$ where a is decreased from 2 to 0 over the course of iterations. When random values of $\vec{A}$are in $[-1,1]$, the next position of a search agent can be in any position between its current position and the position of the prey. The GWO algorithm allows its search agents to update their position based on the locations of the alpha, beta, and delta.

3.2.4 Search for prey (exploration)

Purpose to emphasize exploration and allows the GWO algorithm in order to search globally, the vector $\vec{A}$ with random values greater than 1 or less than -1 to oblige the search agent to diverge from the prey and the $\vec{C}$ vector containing random values in [0, 2]. This component provides random weights for prey in order to stochastically emphasize $(C > 1)$ or deemphasize $(C < 1)$ the effect of prey in defining the distance in Eq. (17).

3.3 WOA algorithm

Whale Optimization Algorithm (WOA) [29 mimics the social behavior of humpback whales. The algorithm is inspired by the bubble-net hunting strategy

3.3.1 Encircling prey

The WOA algorithm assumes that the current best candidate solutions are the target prey or close to the optimum and they try to update their positions towards the best search agent.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)\right| \quad (24)$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \quad (25)$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X^*}$ is the position vector of the best solution obtained so far, $\vec{X}$ is the position vector, $|\ \ |$ is the absolute value. It is worth mentioning here that X^* should be updated in each iteration if there is a better solution.

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (26)$$

$$\vec{C} = 2.\vec{r} \quad (27)$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations (in both exploration and exploitation phases) and $\vec{r}$ is random vector in $[0,1]$.

3.3.2 Bubble-net attacking method (exploitation phase)

The bubble-net behavior of humpback whales described under two mechanisms: Shrinking encircling mechanism and Spiral updating position. The mathematical model is as follows:

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D}, & if\ p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t), & if\ p \geq 0.5 \end{cases} \quad (28)$$

Where p is a random number in $[0,1]$

3.3.3 Search for prey (exploration phase)

The mathematical model of search for prey:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\right| \quad (29)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \quad (30)$$

where $\overrightarrow{X_{rand}}$ is a random position vector (a random whale) chosen from the current population.

3.4 Optimization Algorithms in WindPRO

According to the literature work the predicted algorithm, that Optimization software uses a heuristic placement algorithm (similar to the greedy algorithm) [37].

3.5 Wind farm layout optimization

Flow chart of wind farm layout optimization is given in Fig. 7.

Step 1: Raw wind data, elevation map, roughness map, onstage map and wind turbine generator, including power curve and Ct curve, are used as input data of WAsP software. The wind farm will be divided into the grid, depending on the area of the wind farm, typical resolution 25m to 250m. WAsP calculations result is a wind resource map, which each grid cell includes main parameters: Weibull-c, Weibull-k, mean wind speed, power density, elevation, sector frequency, AEP.

Step 2: Wind resource map are used as input data of windPRO, PSO, GWO, WOA for wind farm layout optimization.

Step 3: All wind layout optimization from Step 2 are calculated and analyzed by WAsP.

Step 4: Conclusions and suitable algorithm proposed for micro-siting wind turbine in wind farm.

4. COMPUTATIONAL STUDIES

This paper proposes three scenarios of wind farm with different assumptions for comprehensive review and evaluates the effectiveness of the algorithm. The scenarios can be summarized as given in Table 1.

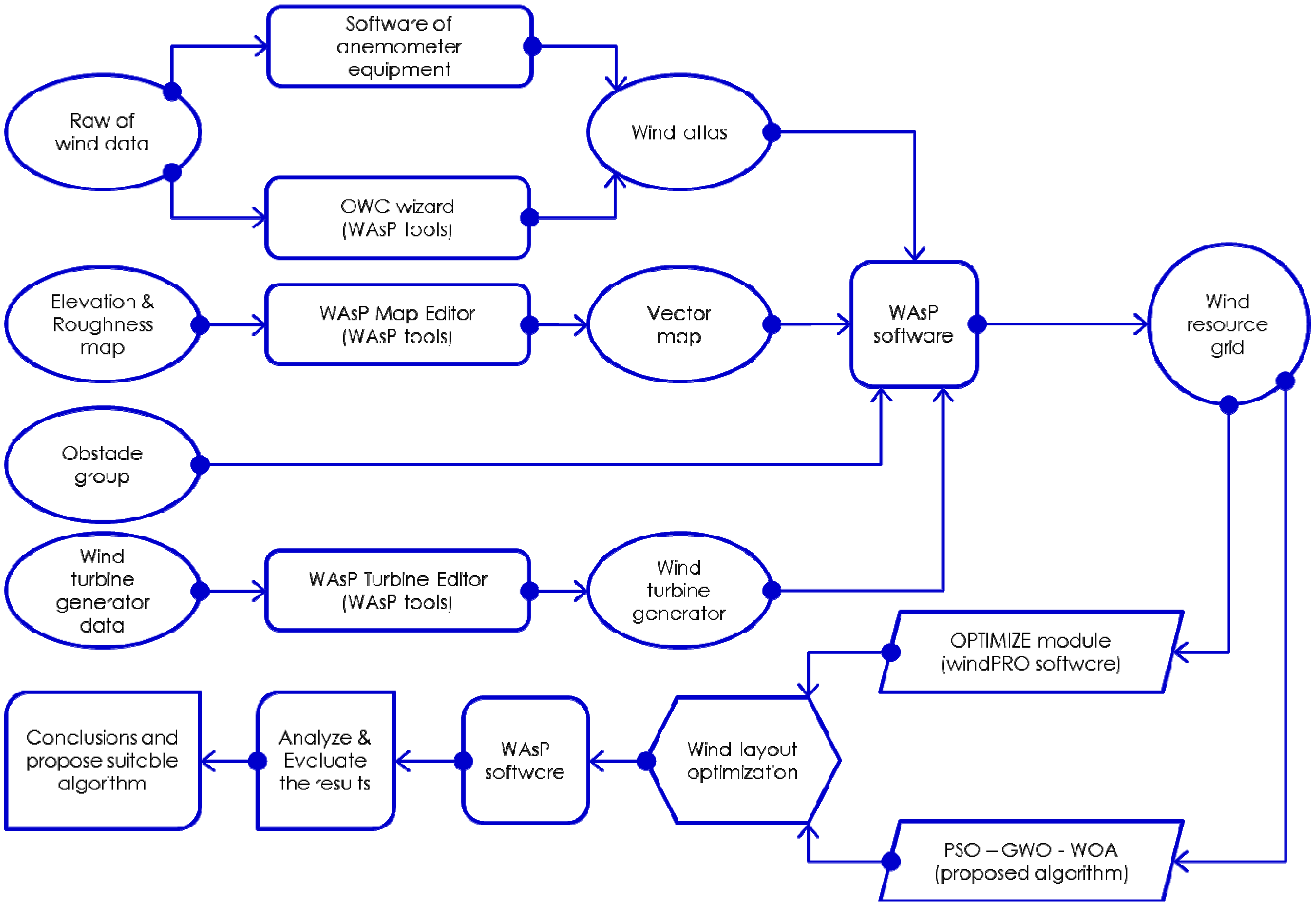


Fig. 7. Flow chart of wind farm layout optimization

Table 1: Summary scenario of wind farm

Explanation	Scenario 1	Scenario 2	Scenario 3
Wind farm	Near-shore	Off-Shore	On-shore
Capacity	5MW	16.8MW	11MW
Wind turbine	5x1MW	10x1.68MW	11x1MW
Boundary	Rectangle boundary	Irregular boundary	Irregular boundary
Data sources	WAsP sample in WAsP software library	Existing wind farm in Vietnam	WAsP sample in WAsP software library

4.1 Scenario 1

Scenario 1 is referred from WAsP workspaces sample, file name Version8Windfarm.wwh. This file includes two wind farms, called as “Good places wind farm” and “Bad places wind farm”. This scenario considered optimal layout for “Bad places wind farm”.

This paper uses available data from WAsP sample (file name Version8Windfarm.wwh) such as wind data, maps, and wind turbine generator.

Source: WAsP workspaces sample.

Wind farm: 5MW (5x1MW)

Wind turbine: 1MW WAsP sample, 1MW, Rotor diameter 54.2m, Hub height 50m.

Power curve and Ct curve: As given in Fig. 5.

Elevation: 146.7m – 158.2m

Boundary: Rectangle

Resolution: 150m

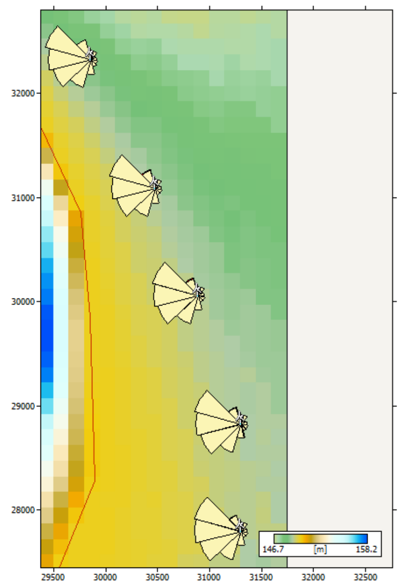


Fig. 8. Wind farm layout, Elevation and gross & wake loss of AEP.

4.1.1 Wind data

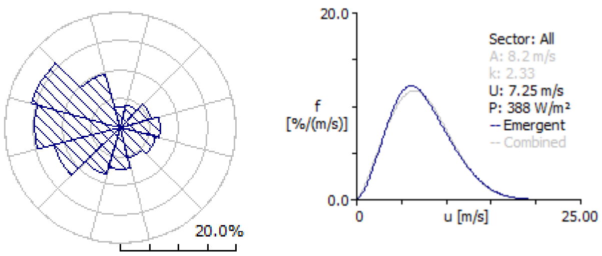


Fig. 9. Wind rose and wind speed distribution.

Fig. 9 shows the prevailing wind direction of sector 9-10-11 from angle 240° to 300° from the north and the highest probability of occurring in wind speed of 6.05 m /s, and accounting for 12.2%.

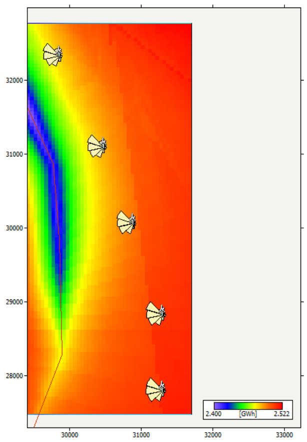


Fig. 10. Wind farm layout from WAsP sample

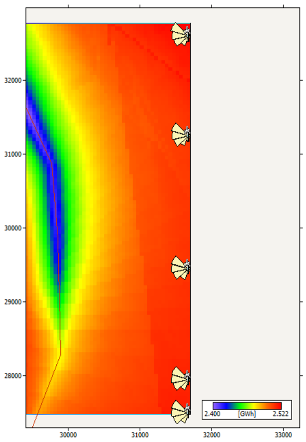


Fig. 11. Wind farm layout optimization by windPRO

Table 2. Result wind farm layout optimization based on WAsP

Method	Gross AEP	Net AEP	Wake loss	Capacity factor
	[GWh]	[GWh]	[%]	[%]
WAsP sample	12.488	12.451	0.29	28.43
windPRO	12.568	12.532	0.29	28.61
PSO	12.561	12.532	0.23	28.61
GWO	12.572	**12.545**	0.22	28.64
WOA	12.565	12.540	0.20	28.63
Comparison of Best Algorithm (GWO) with:				
WAsP sample	0.67%	**0.75%**	-0.07	0.21
windPRO	0.03%	**0.10%**	-0.07	0.03

Wind farm simulation by WAsP shown in Fig. 10 for wind farm layout from WAsP sample and Fig. 11 for wind farm layout optimization by windPRO. To ensure the AEP be the maximum, the turbines are positioned in highest power density of wind resource grid and arranged the wind turbines to avoid prevailing wind direction purpose aiming to reduce the wake effect. It is easy to find from wind farm layout in Fig. 11.

Wind farm layout optimized by the proposed algorithm and windPRO is recalculated in WAsP. Result as given in Table 2, the GWO is the best solution for Scenario 1. Wind farm layout optimization by GWO net AEP is higher than windPRO 0.10% and WAsP sample 0.75%. Further, the gross AEP is highest 12.572 GWh and wake loss is relatively low with 0.22%.

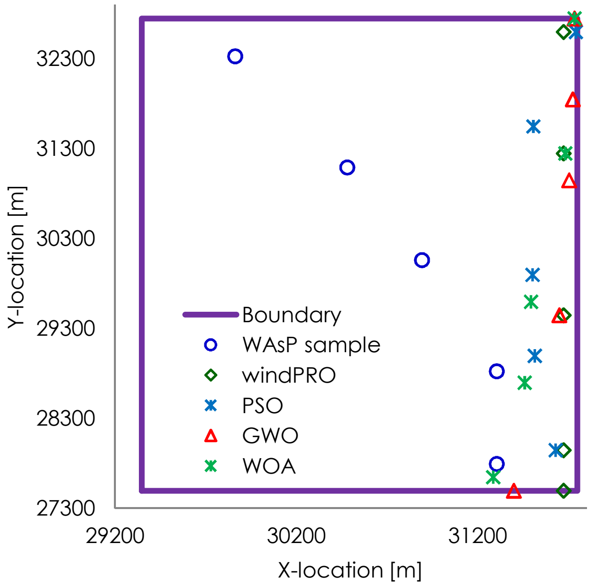


Fig. 12 – Wind farm layout of all algorithms.

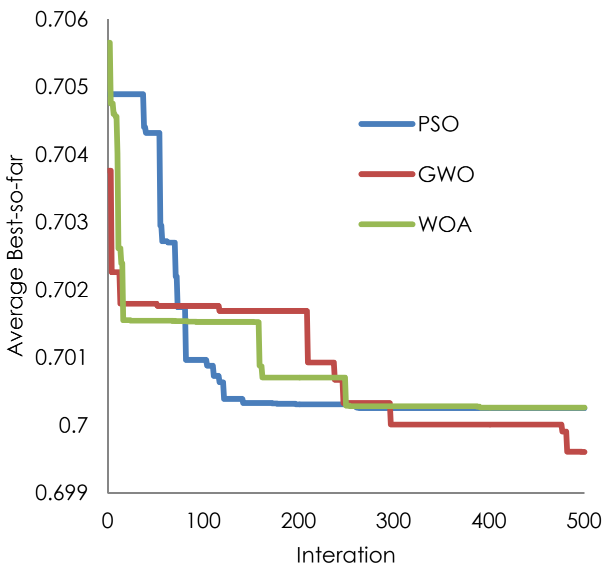


Fig. 13. Convergence curve.

Result in Table 3 shows that AEP model proposed in this article with deviation maximum -1.63% of net AEP and 1.55% wake loss compared to WAsP. This demonstrates that computational models to ensure consistent and accurate relatively. The proposed algorithm can be able competitive results with windPRO (GWO and WOA provide better results). The wind turbines in the wind farm layout (Fig. 14, Fig. 15 and Fig. 16) are nearly identical to windPRO in Fig. 11.

Table 3. Result of Scenario 1 of wind farm.

Scenario 1. Waspdale-Bad places wind farm		WAsP sample	windPRO	PSO	GWO	WOA
Project Calculation	Gross AEP [GWh]	12.466	12.559	12.552	12.546	12.549
	Net AEP [GWh]	12.362	12.328	12.510	12.506	12.510
	Wake loss [%]	0.83	1.84	0.33	0.32	0.32
	Capacity factor [%]	28.22	28.15	28.56	28.55	28.56
WAsP Calculation	Gross AEP [GWh]	12.488	12.568	12.561	12.572	12.565
	Net AEP [GWh]	12.451	12.532	12.532	12.545	12.540
	Wake loss [%]	0.29	0.29	0.23	0.22	0.20
	Capacity factor [%]	28.43	28.61	28.61	28.64	28.63
Comparison (Project with WAsP) Calculation	[%] Gross AEP	-0.18	-0.07	-0.07	-0.20	-0.12
	[%] Net AEP	-0.72	**-1.63**	-0.18	-0.31	-0.24
	[±%] Wake loss	0.54	**1.55**	0.10	0.10	0.12
	[±%] Capacity factor	-0.20	-0.47	-0.05	-0.09	-0.07
Comparison of Proposal algorithm with WAsP sample wind farm based on WAsP		N/A	0.65%	0.65%	**0.75%**	0.71%
Comparison of Proposal algorithm with windPRO based on WAsP		-0.65%	N/A	0.00%	**0.10%**	0.06%

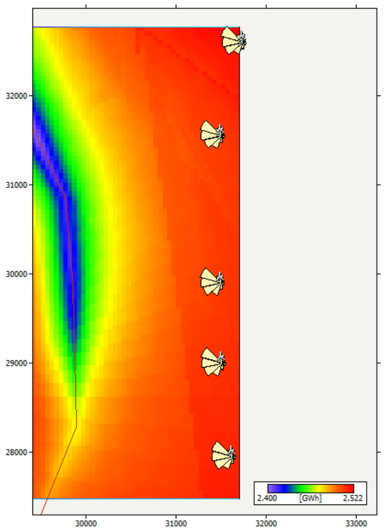


Fig. 14. Wind farm layout by PSO

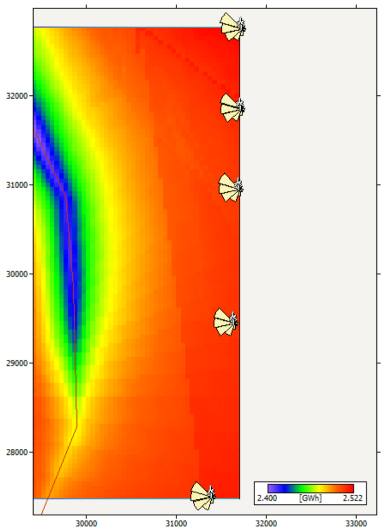


Fig. 15. Wind farm layout by GWO

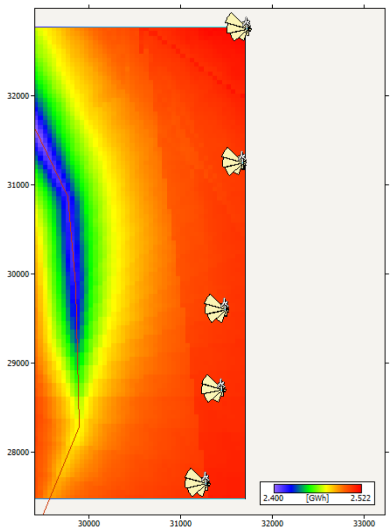


Fig. 16. Wind farm layout by WOA

4.2 Scenario 2

Scenario 2 is existing near shore wind farm in Vietnam. The wind farm data presented in this study are the actual project data.

Fig. 18 shows the prevailing wind direction is of sector 3-9-10 from angle 60^o, 240^o and 270^o from the north and the highest probability of occurring in wind speed of 5.27 m /s, accounting for 11.6%.

Table 4 shows GWO is best result (net AEP 65.708 GWh), higher than that of the windPRO 0.15%. Although wind farm layout by GWO with gross AEP -0.98% lower, but wake effect reduced -1.08% therefore the capacity factor of wind farm is higher 0.07%. The GWO optimal wind farm layout is better than the existing wind farm with 3.69% of net AEP.

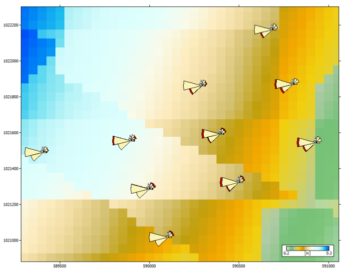
Source: Existing near-shore wind farm in Vietnam.	
Wind farm: 16.8MW (10x1.68MW)	
Wind turbine: GE 1.68-82.5, 1.68MW, Rotor diameter 82.5m, Hub height 86m.	
Power curve and Ct curve: As given in Fig. 6.	
Elevation: 0.2m – 0.3m	
Boundary: Irregular	
Resolution: 50m	

Fig. 17. Wind farm layout, Elevation and AEP gross & wake loss

4.2.1 Wind data

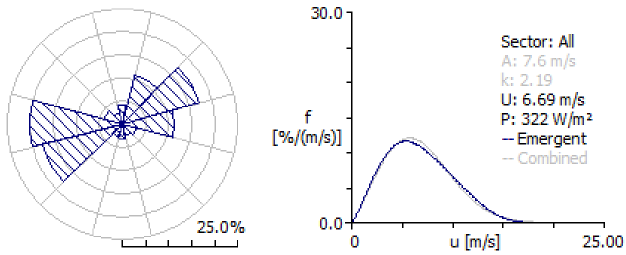


Fig. 18. Wind rose and wind speed distribution

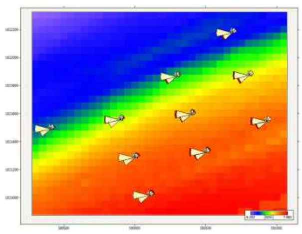


Fig. 19. Existing Wind farm layout

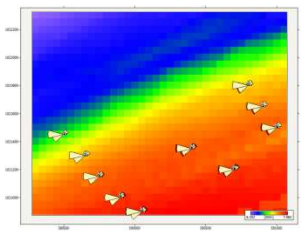


Fig. 20. Wind farm layout optimization by windPRO

Result in Table 5 is compared to WAsP, model calculations of this paper to misleading results maximum -2.85% of net AEP and 2.87% of wake loss. This demonstrates that computational models to ensure consistent and accurate relative. The GWO algorithm can be able competitive results with windPRO. The wind turbines in the wind farm layout (Fig. 23, Fig. 24 and Fig. 25) are nearly identical to windPRO in Fig. 20. The wind turbines find locations with highest power density and optimal layout avoiding wake effect.

Table 4. Result of wind farm layout optimization based on WAsP

Method	Gross AEP	Net AEP	Wake loss	Capacity factor
	[GWh]	[GWh]	[%]	[%]
Existing	67.945	63.369	6.73	43.06
windPRO	69.144	65.608	5.11	44.58
PSO	68.299	65.159	4.60	44.28
GWO	68.468	**65.708**	4.03	44.65
WOA	67.993	65.301	3.96	44.37
Comparison of Best Algorithm (GWO) with:				
Existing	0.77%	**3.69%**	-2.70	1.59
windPRO	-0.98%	**0.15%**	-1.08	0.07

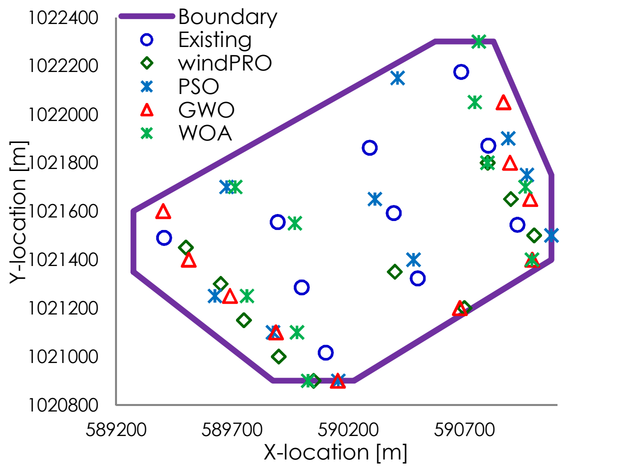


Fig. 21. Wind farm layout of all algorithms.

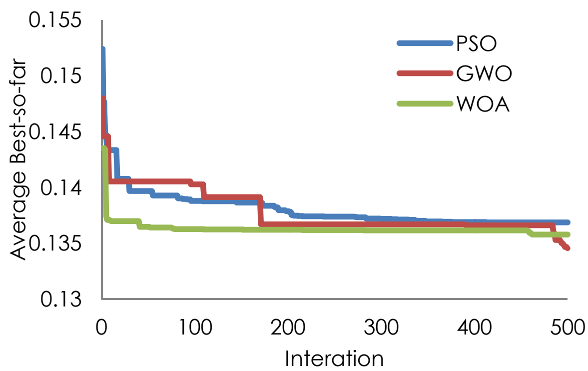


Fig. 22. Convergence curve.

4.3 Scenario 3

Scenario 3 using data sources same as of Scenario 1. However, the Scenario 3 considers optimization for wind farm layout consisting of two areas is “Good places wind farm” and “Bad places wind farm”. It means that the Scenario 3 optimization for wind farm layout with irregular boundary for several separate areas. We call “Wasp dale wind farm”.

Table 5: Result of Scenario 2 of wind farm

Scenario 2. Existing wind farm		**Existing**	**windPRO**	**PSO**	**GWO**	**WOA**
Project Calculation	Gross AEP [GWh]	68.024	69.267	68.292	68.483	67.977
	Net AEP [GWh]	61.720	63.738	63.957	64.758	64.519
	Wake loss [%]	9.27	7.98	6.35	5.44	5.09
	Capacity factor [%]	41.94	43.31	43.46	44.00	43.84
WAsP Calculation	Gross AEP [GWh]	67.945	69.144	68.299	68.468	67.993
	Net AEP [GWh]	63.369	65.608	65.159	65.708	65.301
	Wake loss [%]	6.73	5.11	4.60	4.03	3.96
	Capacity factor [%]	43.06	44.58	44.28	44.65	44.37
Comparison (Project with WAsP) Calculation	[%] Gross AEP	0.12	0.18	-0.01	0.02	-0.02
	[%] Net AEP	-2.60	**-2.85**	-1.84	-1.45	-1.20
	[±%] Wake loss	2.54	**2.87**	1.75	1.41	1.13
	[±%] Capacity factor	-1.12	-1.27	-0.82	-0.65	-0.53
Comparison of Proposal algorithm with Existing wind farm based on WAsP		N/A	3.53%	2.82%	**3.69%**	3.05%
Comparison of Proposal algorithm with windPRO based on WAsP		-3.41%	N/A	-0.68%	**0.15%**	-0.47%

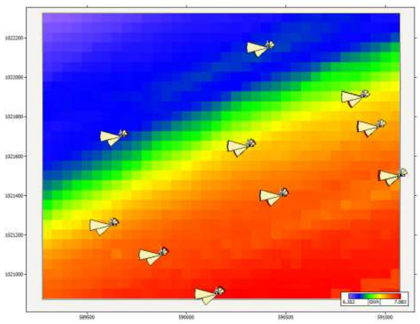


Fig. 23. Wind farm layout by PSO

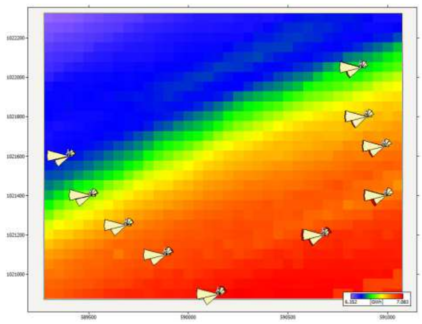


Fig. 24. Wind farm layout by GWO

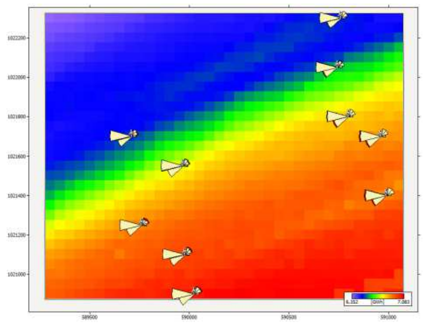


Fig. 25. Wind farm layout by WOA

Table 6. Result of wind farm layout optimization based on WAsP.

Method	Gross AEP	Net AEP	Wake loss	Capacity factor
	[GWh]	[GWh]	[%]	[%]
WAsP sample	30.126	30.066	0.20	31.20
windPRO	32.520	**32.342**	0.55	33.56
PSO	32.088	31.904	0.58	33.11
GWO	32.105	**31.921**	0.57	33.13
WOA	32.072	31.864	0.65	33.07
Comparison of Best Algorithm (GWO) with:				
WAsP sample	6.57%	**6.17%**	0.37	1.93
windPRO	-1.28%	**-.30%**	0.02	-0.44

Scenario 3 is the challenge for this study, the optimum layout of on-shore wind farm (elevation difference of 203.3m). The result, windPRO is best optimization algorithm. However, GWO also results in competition, less than -1.3% to windPRO compared to net AEP.

In the proposed algorithms (PSO, GWO, WOA), GWO is still optimal algorithm. Wind farm layout by GWO gives higher AEP than WAsP sample wind farm 6.17%.

Note that, Fig. 30 PSO algorithm with the best fitness. Indeed, the calculated results from this paper (Project calculation) in Table 7 shows that AEP of PSO – 31.809 GWh, GWO – 31.745 GWh and WOA – 31.595 GWh. It is due to the mathematical model from this study and WAsP perhaps not to be quite the same.

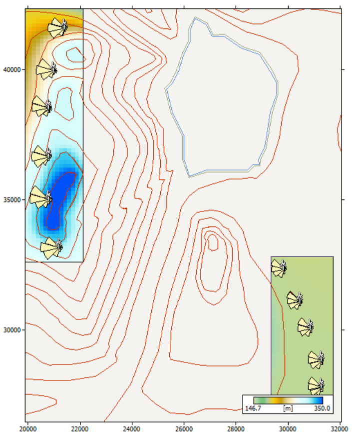
Source: WAsP workspaces sample.	
Wind farm: 11MW (11x1MW)	
Wind turbine: 1MW WAsP sample, 1MW, Rotor diameter 54.2m, Hub height 50m.	
Power curve and Ct curve: As given in Fig. 5.	
Elevation: 146.7m – 350.0m	
Boundary: Irregular, tow areas.	
Resolution: 150m	

Fig. 26. Wind farm layout, Elevation and gross & wake loss of AEP.

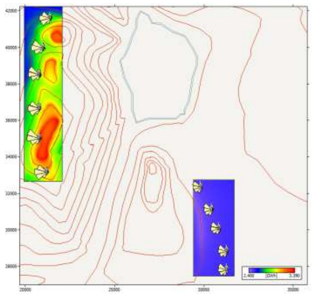


Fig. 27. Wind farm layout from WAsP sample

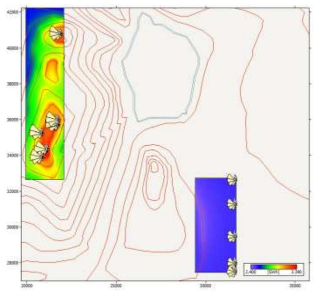


Fig. 28. Wind farm layout optimization by windPRO

Result in Table 7. Compared to WAsP, the model calculation from this paper is misleading results maximum -1.62% of net AEP and 1.54% of wake loss. The wind turbines in the wind farm layout (Fig. 31, Fig. 32 and Fig. 33) are nearly identical to windPRO in Fig. 28. The wind turbines find locations with highest power density and optimal layout avoiding wake effect.

4.4 Result Evaluation

Wind energy production modeling of this study is maximum 2.85% of net AEP (Scenario 2 – Existing wind farm in Vietnam) different to WAsP, which is possible error due to uncertainties factor, windPRO default decrease in calculated energy due to uncertainties is 10%. Therefore, computational models of this study fit the actual application.

For evaluating the effectiveness of algorithms, this paper implemented calculations for 500 interactions with over 20 independent runs, the result of average and standard deviation as given in Table 8.

The averages in Table 8 and best solutions obtained (Table 2, Table 4 and Table 6) found that the results of the run-time convergence are stable, the proposed algorithm to find optimal results. GWO is the algorithm that is highly suitable for solving wind farm layout optimization problems.

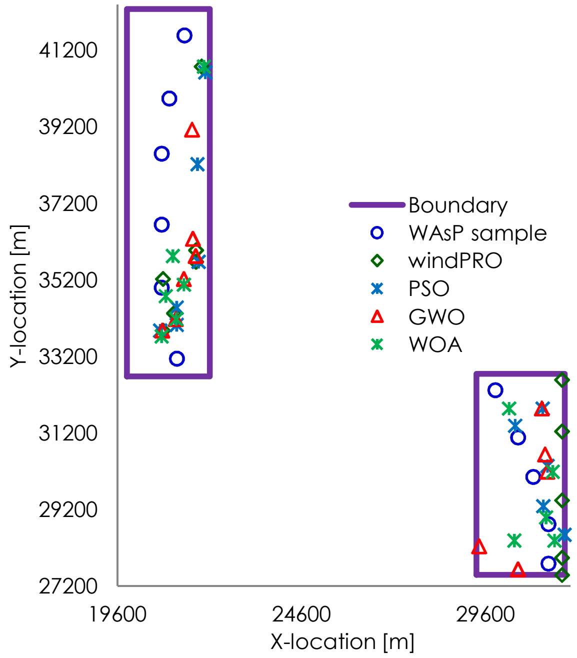


Fig. 29. Wind farm layout of all algorithms.

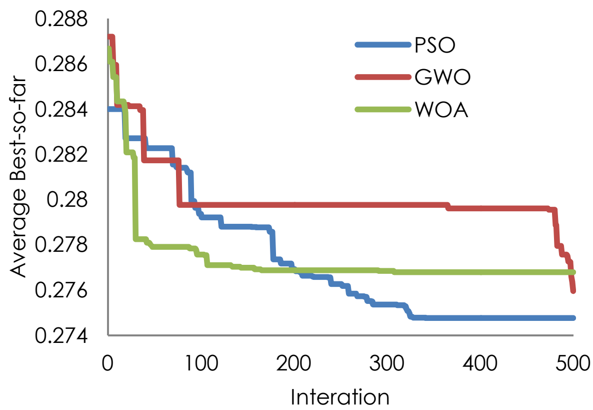


Fig. 30. Convergence curve.

4.5 Result evaluation

Wind energy production modeling of this study is maximum 2.85% of net AEP (Scenario 2 – Existing wind farm in Vietnam) different to WAsP, which is possible error due to uncertainties factor, windPRO default decrease in calculated energy due to uncertainties is 10%. Therefore, computational models of this study fit the actual application.

For evaluating the effectiveness of algorithms, this paper implemented calculations for 500 interactions with over 20 independent runs, the result of average and standard deviation as given in Table 8.

Table 7 – Result of Scenario 3 of wind farm

Scenario 3. Waspdale wind farm		WAsP sample	windPRO	PSO	GWO	WOA
Project Calculation	Gross AEP [GWh]	30.151	32.496	32.137	32.075	32.011
	Net AEP [GWh]	29.887	31.817	**31.809**	31.745	31.595
	Wake loss [%]	0.87	2.09	1.02	1.03	1.30
	Capacity factor [%]	31.02	33.02	33.01	32.94	32.79
WAsP Calculation	Gross AEP [GWh]	30.126	32.520	32.088	**32.105**	32.072
	Net AEP [GWh]	30.066	32.342	31.904	**31.921**	31.864
	Wake loss [%]	0.20	0.55	0.58	0.57	0.65
	Capacity factor [%]	31.20	33.56	33.11	33.13	33.07
Comparison (Project with WAsP) Calculation	[%] Gross AEP	0.08	-0.08	0.15	-0.09	-0.19
	[%] Net AEP	-0.59	**-1.62**	-0.30	-0.55	-0.84
	[±%] Wake loss	0.67	**1.54**	0.44	0.46	0.65
	[±%] Capacity factor	-0.19	-0.55	-0.10	-0.18	-0.28
Comparison of Proposal algorithm with WAsP sample wind farm based on WAsP		N/A	7.57%	6.11%	**6.17%**	5.98%
Comparison of Proposal algorithm with windPRO based on WAsP		-7.04%	N/A	-1.35%	**-1.30%**	-1.48%

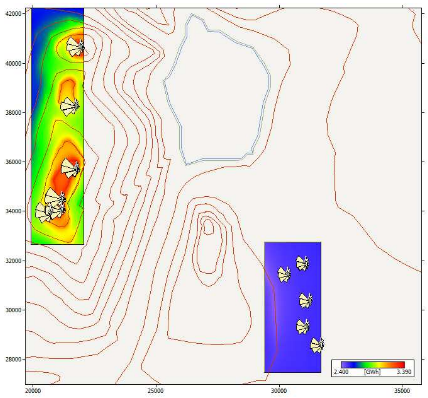


Fig. 31. Wind farm layout by PSO

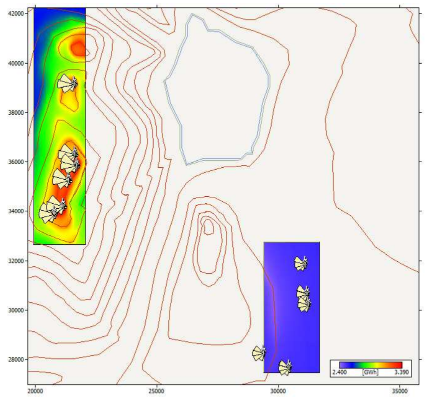


Fig. 32. Wind farm layout by GWO

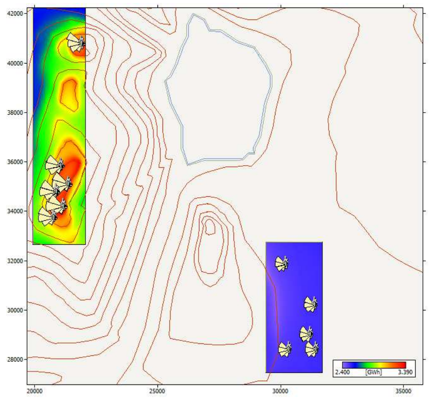


Fig. 33. Wind farm layout by WOA

The averages in Table 8 and best solutions obtained (Table 2, Table 4 and Table 6) found that the results of the run-time convergence are stable, the proposed algorithm to find optimal results. GWO is the algorithm that is highly suitable for solving wind farm layout optimization problems.

However, the average and standard deviation only can compare to the overall performance of algorithms. In addition, statistical test is applied to confirm the significance of the result based on every single runs. The Wilcoxon rank-sum test is a non-parametric test in statics that can be used to determine if two sets of solutions (population) are different statistically significant or not. In this paper an algorithm is statistically significant if and only if it results in a p-value of Wilcoxon rank-sum test less than 0.05 [32].

The p-values in Table 9 show the proposed algorithm in this paper are statistically significant.

Seyedali Mirjalili et al. [30] in their study demonstrated that the GWO was able to provide highly competitive results compared to well-known heuristics (GA, PSO, DE, EP and ES). This paper is also found that the appropriateness of applying GWO algorithm to solve practical problems of wind farm layout optimization. Therefore, the GWO algorithm is the recommendation of this paper.

Table 8 – Result of Average and Standard deviation

Method / Scenario (Based on Net AEP)		Scenario 1.	Scenario 2.	Scenario 3.
windPRO	Avg.	12.328	63.738	**31.817**
	Std.	0	0	0
	Min value	12.328	63.738	31.817
	Max value	12.328	63.738	31.817
PSO	Avg.	12.487	63.234	**31.589**
	Std.	0.012	0.429	0.147
	Min value	12.470	62.402	31.333
	Max value	12.510	64.006	31.882
GWO	Avg.	**12.507**	**64.164**	31.403
	Std.	0.010	0.667	0.117
	Min value	12.479	62.985	31.227
	Max value	12.521	65.110	31.745
WOA	Avg.	12.490	63.630	31.262
	Std.	0.012	0.491	0.217
	Min value	12.469	62.531	30.712
	Max value	12.510	64.519	31.649

Table 9: p-values of the Wilcoxon ranksum test over all runs

Scenario	windPRO	PSO	GWO	WOA
1	N/A	3.273E-09	3.295E-09	2.94E-09
2	N/A	5.076E-05	2.915E-06	0.0295217
3	N/A	4.045E-05	1.552E-06	1.66E-06

5. Conclusion

This paper has solved wind farm layout optimization problems base on recent algorithms and propose applying the GWO. The GWO algorithm has proven efficacy to solve practical problems and optimal position of wind turbines in the wind farm to be a typical illustration. Wind energy production modeling of this study is maximum of 2.85% of net AEP deviation compared to that of WAsP and optimum wind farm layout compete with windPRO result. This study is consistent application for the actual wind farm design.

Improvements wake effects modeling for on-shore wind farm are proposed continuing research in the future.

ACKNOWLEDGEMENTS

This research is funded by Ho Chi Minh City University of Technology (HCMUT) under grant number TSĐH-2015-ĐĐT-50.

REFERENCES

[1] Javier Serrano González, Manuel Burgos Payán, Jesús Manuel Riquelme Santos, Francisco González-Longatt. A review and recent developments in the optimal wind-turbine micro-siting problem. Renewable and Sustainable Energy Reviews 2014; 30: 133–144.

[2] Jensen N.O. A note on wind generator interaction. Technical report Riso-M-2411; 1983.

[3] [3] Katic I, Højstrup J, Jensen N. A simple model for cluster efficiency. In: EWEC 86; 1986.

[4] [4] Mosetti G, Poloni C, Diviacco B. Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm. Journal of Wind Engineering and Industrial Aerodynamics 1994;51:105–16.

[5] Aytun Ozturk U, Norman BA. Heuristic methods for wind energy conversion system positioning. Electric Power Systems Research 2004;70:179–85.

[6] [6] Grady SA, Hussaini M, Abdullah MM. Placement of wind turbines using genetic algorithms. Renewable Energy 2005;30:259–70.

[7] Marmidis G, Lazarou S, Pyrgioti E. Optimal placement of wind turbines in a wind park using Monte Carlo simulation. Renewable Energy 2008;33: 1455–60.

[8] Şişbot S, Turgut Ö, Tunç M, Çamdalı Ü. Optimal positioning of wind turbines on Gökçeada using multi-objective genetic algorithm. Wind Energy 2010;13:297–306.

[9] Wan C, Wang J, Yang G, Zhang X. Optimal micro-siting of wind farms by particle swarm optimization. Anonymous advances in swarm intelligence. Springer; 2010; 198–205.

[10] Kusiak A, Song Z. Design of wind farm layout for maximum wind energy capture. Renewable Energy 2010;35:685–94.

[11] Saavedra-Moreno B, Salcedo-Sanz S, Paniagua-Tineo A, Prieto L, Portilla-Figueras A. Seeding evolutionary algorithms with heuristics for optimal wind turbines positioning in wind farms. Renewable Energy 2011;36:2838–44.

[12] Archer R, Nates G, Donovan S, Waterer H. Wind turbine interference in a wind farm layout optimization mixed integer linear programming model. Wind Engineering 2011; 35:165–75.

[13] Eroğlu Y, Seçkiner SU. Design of wind farm layout using ant colony algorithm. Renewable Energy 2012;44:53–62.

[14] Wagner M, Day J, Neumann F. A fast and effective local search algorithm for optimizing the placement of wind turbines. Renewable Energy 2013; 51:64–70.

[15] Jagabondhu Hazra, Subhadip Mitra, Sathyajith Mathew, Fauzi Zaini. 3D layout optimization for large wind farms. In: ISGT, 2015 IEEE Power & Energy Society.

[16] Arne Kleina. A continuously differentiable turbine layout optimization model for offshore wind farms. Energy Procedia 2016; 94:497–503.

[17] Prateek Mittal, Kedar Kulkarni, Kishalay Mitra. A Novel and Efficient Hybrid Optimization Approach for Wind Farm Micro-siting. IFAC-PapersOnLine 2015; 48-8:397-402.
[18] Huan Long, Zijun Zhang. A Two-Echelon Wind Farm Layout Planning Model. In: IEEE Transactions on Sustainable Energy 2015; 6:863-871.
[19] Jinkyoo Park, Kincho H. Law. Layout optimization for maximizing wind farm power production using sequential convex programming. Applied Energy 2015; 151: 320–334.
[20] Javier Serrano Gonza'lez, Manuel Burgos Paya'n, Jesús Riquelme Santos, A'ngel Gaspar Gonza'lez Rodríguez. Maximizing the overall production of wind farms by setting the individual operating point of wind turbines Renewable Energy 2015; 80: 219-229.
[21] Peng Hou, Weihao Hu, Cong Chen, Mohsen Soltani, Zhe Chen. Optimization of offshore wind farm layout in restricted zones. Energy 2016; 113:487-496.
[22] Peng Hou, Weihao Hu, Mohsen Soltani, Zhe Chen. Optimized Placement of Wind Turbines in Large-Scale Offshore Wind Farm Using Particle Swarm Optimization Algorithm. In: IEEE Transactions on Sustainable Energy 2015; 6:1272-1282.
[23] Zhe Song, Zijun Zhang, Xingying Chen. The decision model of 3-dimensional wind farm layout design. Renewable Energy 2016; 85:248-258.
[24] Shafiqur Rehman, S. S. A. Ali. Wind Farm Layout Design using Modified Particle Swarm Optimization Algorithm. in: Renewable Energy Congress (IREC), 2015 6th International.
[25] Rabia Shakoor, Mohammad Yusri Hassan, Abdur Raheem, Nadia Rasheed, Mohamad Na’im Mohd Nasir. Wind Farm Layout Optimization by Using Definite Point Selection and Genetic Algorithm. In: Power and Energy (PECon), 2014 IEEE International Conference on.
[26] Jim Y.J. Kuo, David A. Romero, J. Christopher Beck, Cristina H. Amon. Wind farm layout optimization on complex terrains – Integrating a CFD wake model with mixed-integer programming. Applied Energy 2016; 178:404–414.
[27] DTU Wind Energy. Wind energy industry-standard software - WAsP. http://www.wasp.dk/. Accessed: 2016-12-02.
[28] WindPRO-EMD International A/S. http://www.emd.dk/windpro/. Accessed: 2016-12-02.
[29] Seyedali Mirjalili, Andrew Lewis. The Whale Optimization Algorithm. Advances in Engineering Software 2016; 95:51–67.
[30] Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis. Grey Wolf Optimizer. Advances in Engineering Software 2014; 69:46–61.
[31] Wolpert DH, Macready WG. No free lunch theorems for optimization. Evolut Comput, IEEE Trans 1997;1:67–82.
[32] Seyedali Mirjalili. http://www.alimirjalili.com/index.html. Accessed: 2016-12-02.
[33] Gary L. Johnson, "Wind Energy Systems”, Manhattan, Kansas State University, 2006.
[34] Rabia Shakoor, Mohammad Yusri Hassan, Abdur Raheem, Yuan-Kang Wu. Wake effect modeling: A review of wind farm layout optimization using Jensen's model. Renewable and Sustainable Energy Reviews 2016; 58: 1048–1059.
[35] M.S. Mohan Raj, M. Alexander, M. Lydia. Modeling of Wind Turbine Power Curve. In: Innovative Smart Grid Technologies - India (ISGT India), 2011 IEEE PES.
[36] Kennedy J, Eberhart R. Particle swarm optimization, in Neural Networks, 1995. In: Proceedings, IEEE international conference on; 1995. p. 1942–1948.
[37] Fagerfjäll P. Optimizing wind farm layout, more bang for the buck using mixed integer linear programming. Department of Mathematical Sciences, Chalmers University of Technology, 2010, Göteborg, Sweden.