A COMPARATIVE ANALYSIS OF 'S' AND 'V' TYPE TRANSFER FUNCTIONS FOR BINARY PARTICLE SWARM OPTIMIZATION ALGORITHM-BASED WIND FARM DESIGN SELECTION PROBLEM

Prasun BHATTACHARJEE[1]

Somenath BHATTACHARYA[2]

Abstract

To check the upsurge of universal average temperature well below 2oC as projected by the Paris Agreement of 2016, renewable energy technologies like wind power must remain commercially feasible for enabling the green energy transition. The current study emphasizes the relevance of the Binary Particle Swarm Optimization method for solving wind farm layout selection problems. The relative efficiency of different transfer functions for attaining the minimum cost of energy has been examined. The research outcomes demonstrate the better competence of 'S' type transfer functions over the 'V' type ones for five terrain situations and wind-flow settings.

Keywords: Wind Power, Wind Farm Design, Binary Particle Swarm Optimization, Transfer Function, Power Generation Cost

JEL Classification: -

1. Introduction

Since universal power generation grew rapidly with the consolidation of industrial pursuits, the fossil fuel stashes are depleting at an exceptional rapidity [1]. Renewable power resources offer thriving substitutes when there is an expanding global trepidation for the insufficient reserve of fossil fuels and their drawbacks on the bionetwork [2]. Global renewable energy utilization and Wind Power Generation (WPG) segment have advanced exponentially since the introductory years of the twenty-first era [3]. Universal collective WPG capacity has grown from 20 GW in 2000 to 650 GW in 2019, estimated to reach 4042 GW by 2050.

Along with lower emission advantage, WPG farms are entailed to function economically [5]. Due to the relatively low capacity of the Wind Turbine (WT), a vast count of WTs is to be instated within a wind farm to accomplish the capability of traditional power plants.

[1] Lecturer, Ramakrishna Mission Shilpapitha, prasunbhatta@gmail.com

[2] Associate Professor, Jadavpur University, snb_ju@yahoo.com

Wind farm design should be prudently evaluated for selecting the most acceptable option that delivers the best possible profit for definite capital spending [6]. Several research works have been executed to resolve the concerns allied to Wind Farm Layout Optimization (WFLO).

Initially, in 1994, WFLO was explored with a Genetic Algorithm (GA) [7]. Since the mid-2000s, GA has been extensively applied to WFLO problems for grid-like discrete as well as coordinate-based continuous representations of wind farms [8]. Grady et al. (2005) [8] employed GA to find the optimum location of WTs for maximizing the power generation capacity whereas reducing the number of WTs and the land usage. Huang (2007) [9] proposed a distributed GA methodology to amplify the yearly profit for bigger wind farms. Elkinton et al. (2008) [10] discussed the application of five diverse kinds of optimization techniques for offshore WFLO. An innovative coding tactic was employed for GA-based WFLO [11].

Chen et al. (2015) [12] employed multi-objective GA for enhancing the power yield while reducing the overall cost of wind power generation farms. Yin et al. (2017) [13] suggested an enhanced GA methodology to reduce the cost of power generation subjected to the uncertainty of wind flow. Particle Swarm Optimization (PSO) algorithm with the Gaussian mutation has been applied for WFLO [14]. Chowdhury et al. (2012) [15] attempted unrestricted WFLO employing constrained PSO.

The BPSO technique with time-varying acceleration coefficients was employed to maximize the generation capacity for a minimum investment [16]. Hou et al. (2016) [17] proposed PSO with multiple adaptive approaches to maximize the generated power. Pillai et al. (2017) [18] engaged both GA and PSO for reducing the Levelized Cost of power generation at the Middelgrunden wind farm in Denmark. PSO is an AI-enabled optimization technique that searches for the most optimal solution by communicating knowledge about universal or local best solutions [19].

Apart from GA and PSO, Monte Carlo simulation has been applied to increase the power output while minimizing the total cost [20]. A Simulated Annealing algorithm has been utilized by Rivas et al. (2009) [21] for offshore WFLO. DuPont et al. (2016) [22] engaged the Pattern Search algorithm to WFLO with steady and inconsistent wind patterns. The heuristic methodology is preferred over mathematical programming because of the multifaceted nature of WPG farm design problems [23, 24]. Although the BPSO technique has been used in WFLO, the relative effect of different transfer functions applied in BPSO has not yet been explored for wind farm design purposes.

The current study has focused on the BPSO technique for the WFLO problem. A grid-like structure of wind farms has been taken into consideration for utilizing the binary coding capability of BPSO. Four ‘S’ and four ‘V’-type transfer functions have been employed simultaneously to evaluate their relative effectivity in finding the least possible power generation cost for five arbitrarily selected terrain and wind flow conditions. This paper has been coordinated as follows. The problem presentation, accessible in segment 2, furnishes a comprehensive depiction of the objective function. The optimization algorithm, 'S', and 'V' type transfer function-related details are obtainable in segment 3. Results and related discussions are accessible in segment 4. Conclusion and future prospect-related discussions are available in segment 5.

2. Problem Presentation

Objective Function Formulation

The rationale of the current research is to optimize the positioning of WTs by minimizing the Cost of Energy (C_E). This WFLO problem is framed through wind flow patterns, wake effect, WT parameters, and allied power generation factors. The present study has engaged the cost function, five arbitrarily chosen terrain conditions, and wind flow models as the benchmarking evaluation setup for assessing the comparative effectiveness of eight different transfer functions of BPSO following [25][26]. The objective function is formulated as:

$$C_E = \frac{\{\gamma * \delta\} + (C_O X)}{(1-(1+k)^{-p})/k} * \frac{1}{8760 * E} + \frac{0.1}{X} \tag{1}$$

$$\gamma = C_A X + C_B floor\left(\frac{X}{Y}\right) \tag{2}$$

$$\delta = \frac{2}{3} + \frac{1}{3} e^{-0.00174 X^2} \tag{3}$$

Where C_A symbolizes the outlay of a WT. C_B represents the expense of a sub-station. X signifies the tally of WTs in a WPG farm, and Y stands for WT per sub-station i.e., 30. Co indicates the operational and maintenance cost per annum. E denotes the power yield of the WPG farm. k symbolizes the percentage of interest. p signifies the lifespan of the wind farm.

The latter term (0.1/X) recompenses the layouts with a higher WT count to make the most of the wind farm's power output. The intent of the current work is to curtail the C_E. The goal function is constrained within the defined limits of the terrain dimensions, and the gap between two adjacent WTs must be at least eight times the WT radius to minimize the wake loss.

If you use subsections, please follow the draft regulations: if you start right after the section declaration, just place the subsection on the next paragraph, if you have a content for the section and then insert a subsection leave 1 (one) empty paragraph above and below the subsection (see below).

3. Optimization Algorithm

Binary Particle Optimization Algorithm (BPSOA)

Due to the complex nature of wind flow scenarios, a heuristic methodology is essential to be adapted for WFLO. In the current research work, BPSOA has been considered for minimizing the C_E in the current study. The optimization algorithm has been discussed in the subsequent sub-sections.

PSO imitates the societal activities of birds, bees, or a shoal of fishes. Every member of the swarm is signified by a vector in the search domain. The algorithm regulates the updating strategy of the swiftness of a swarm member known as a ‘particle’ correspondingly. The PSO procedure repeats up to a preset number of counts or till an acceptable level of error is attained [27].

A ‘particle’ can be categorized as a bit sequence in BPSO. The spot of a ‘particle’ can be revised by swapping between 0 and 1 according to the velocity [28].

For the n^{th} bit of m^{th} particle, the velocity v_{mn} is computed as per Eq. (4) and (5),

$$v_{mn} = wv_{mn} + \tau \tag{4}$$

$$\tau = c_1 r_{1n}(p_{mn} - x_{mn}) + c_2 r_{2n}(g_n - x_{mn}) \tag{5}$$

where w signifies the inertia weight with a value ranging between 0 and 1. w can be computed according to a linearly declining technique as per Eq. (6).

$$w = w_{max} - (w_{max} - w_{min})\frac{k}{L} \tag{6}$$

where w_{max} and w_{min} are the supreme and least confines of inertia weight respectively. k stands for the current counts of repetition and L denotes the maximum count of repetitions. c_1 and c_2 are non-negative acceleration parameters. r_{1n} and r_{2n} are arbitrary variables following uniform distribution with values ranging between 0 and 1.

P_{mn} indicates the nth bit of the individual preeminent location of the m^{th} particle. g_n represents the n^{th} bit of the universal paramount location.

The transfer function which is used to update the value of the bit has been defined in Eq. (7).

$$v_{mn} = \frac{1}{1+e^{-v_{mn}}} \tag{7}$$

The value of the bit is updated as per Eq. (8).

$$x_{mn} = \begin{cases} 1, & if\ rand() \le s(v_{mn}) \\ 0, & otherwise \end{cases} \tag{8}$$

Where rand() arbitrarily generates a number ranging between 0 and 1 with uniform distribution [28].

The algorithm of the proposed BPSO has been presented in Table 1, where present locations, individual best locations, and universal best locations have been signified as $x_m = (x_{m1}, \ldots\ldots, x_{mn})$, pm = $(p_{m1}, \ldots\ldots, p_{mn})$ and $g = (g_1, \ldots\ldots, g_n)$ respectively.

Arbitrarily create a preliminary population
Arbitrarily create the primary velocities in the interior of the velocity limits
repeat
for m = 1 to Populace Limit **do**
if f $(\mathbf{x_m})$ < f $(\mathbf{p_m})$ **then** $\mathbf{p_m} = \mathbf{x_m}$;
if f $(\mathbf{p_m})$ < f $(\mathbf{g})$ **then** $\mathbf{g} = \mathbf{p_m}$;
end
for m = 1 to Populace Limit **do**
for n = 1 to Particle Bit Limit **do**
Compute **w** with Eq. (6)
Revise velocity using Eq. (4) and (5)
Revise location with Eq. (7) and Eq. (8)
end
end
until the Ending criteria are attained

Table 1. Algorithm for BPSO [28]

The transfer function depicts the possibility of altering location vector particles between 0 and 1.

The transfer function must be capable enough to offer a superior possibility of altering the location for a sizeable amount of particle velocity. It must also tender a minor possibility of shifting the location for a lesser quantity of particle velocity [29] [30].

Serial No.	**Transfer Function**
S_1	$S(x) = \frac{1}{1 + e^{-2x}}$
S_2	$S(x) = \frac{1}{1 + e^{-x}}$
S_3	$S(x) = \frac{1}{1 + e^{-\frac{x}{2}}}$
S_4	$S(x) = \frac{1}{1 + e^{-\frac{x}{3}}}$

Table 2. ‘S’ Type Transfer Functions [29]

Serial No.	**Transfer Function**
V_1	$S(x) = \left\lvert \operatorname{erf}\left(\frac{\sqrt{\pi}}{2}x\right) \right\rvert = \left\lvert \frac{\sqrt{2}}{\pi} \int_0^{\frac{\sqrt{\pi}}{2}x} e^{-t^2}\, dt \right\rvert$
V_2	$S(x) = \lvert \tanh(x) \rvert$
V_3	$S(x) = \left\lvert \frac{x}{\sqrt{1 + x^2}} \right\rvert$
V_4	$S(x) = \left\lvert \frac{2}{\pi} arc \tan\left(\frac{\pi}{2}x\right) \right\rvert$

Table 3. ‘V’ Type Transfer Functions [29]

These transfer functions can be classified as ‘S’-shaped and ‘V’-shaped according to their graphical plots [31].

Four ‘S’ and four ‘V’ type transfer functions used for BPSO have been mentioned in Tables 2 and 3, respectively. Their graphical plots have been shown in Figs. 1 and 2 correspondingly.

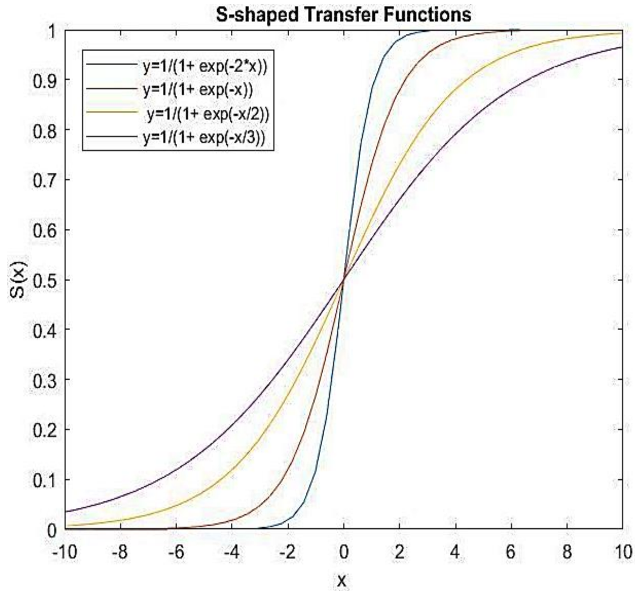

Figure 1. Plots of ‘S’ Type Transfer Functions [31]

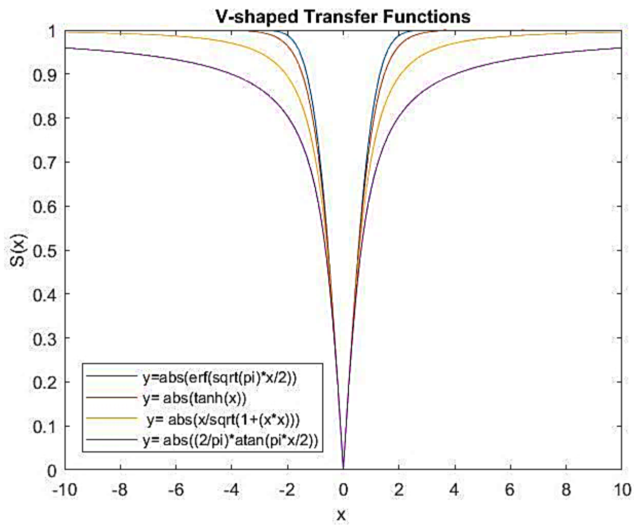

Figure 2. Plots of ‘V’ Type Transfer Functions [31]

The transfer functions engaged for BPSO are influential in providing the appropriate probability according to the absolute velocity of a particle [30]. The choice of the competent transfer function can facilitate the decision-makers to explore the search domain (terrain) most efficiently and locate the best possible emplacement of the WTs in a WPG farm for achieving the least possible C_E [32]-[35].

4. Results and Discussion

For appraising the proportional performance of 'S' and 'V' type transfer functions for the WFLO problem, a similar CE function, described in section 2, has been employed. CE has been measured in USD/kWh. A terrain condition considered by Wilson et al. (2018) is put into operation as a benchmark terrain situation in contemporary research and it is shown in Fig. 3.

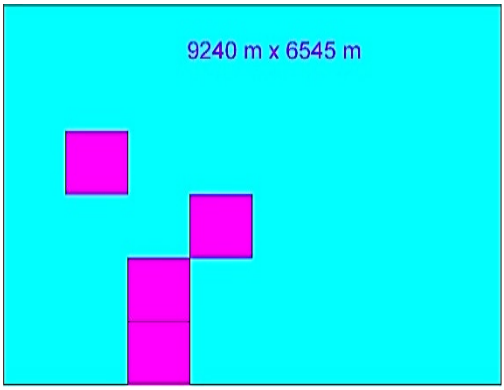

Figure 3. Considered Terrain Setting

The rectangular terrain of length and breadth of 9240 m and 6545 m respectively has been deemed in the existing study. The area shown in blue is available for positioning WTs whereas the area shown in pink indicates the obstructions inside the terrain. WTs cannot be placed within the obstruction area. The airflow scenario spread across directional angles (shown as 0 to 345) held in the present work is graphically represented in Fig. 4 [36]-[40].

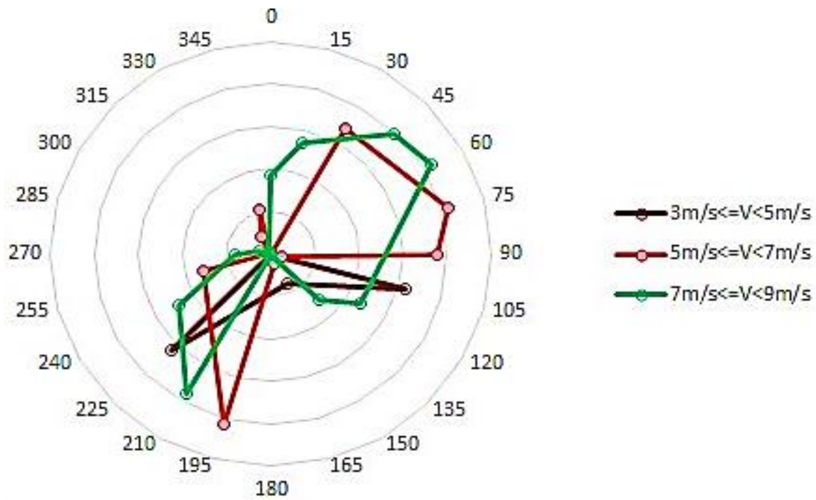

Figure 4. Considered Airflow Condition

The parameter setting for the WFLO problem has been presented in Table 4, and experimentation outcomes have been displayed in Fig. 5. The minimum CE has been specified in bold form.

Parameter	**Considered Value**
Operational Charge	USD 20,000
c_1	2
c_2	2
Diameter of WT	77m
Number of Iterations	50
Operative Period	20 Years
Population Size	20
Rate of Interest	3%
Rated Power	1500 kW
Sub-Station Outlay	USD 8,000,000
v_{max}	6
w	2
w_{max}	0.9
w_{min}	0.4
WT Outlay	USD 750,000

Table 4. Parameter Settings

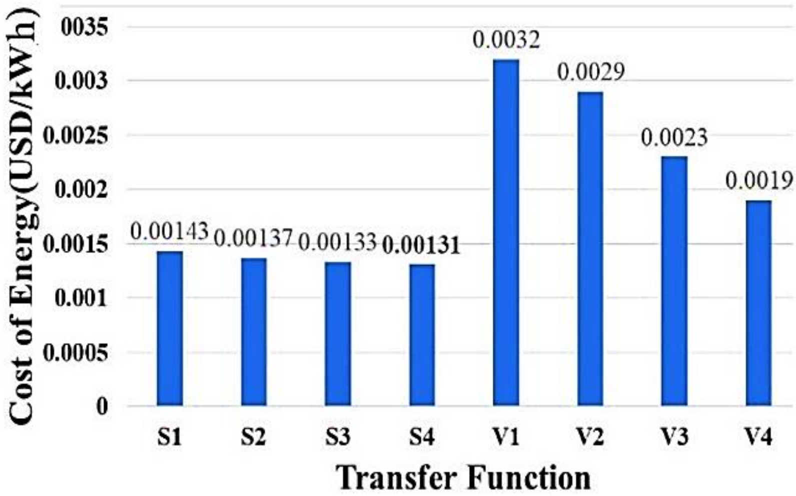

Figure 5. Comparison of Optimized Costs of Energy

Transfer Function	**Cost of Energy (USD/kWh)**
S_1	0.00143
S_2	0.00137
S_3	0.00133
S_4	0.00131
V_1	0.00320
V_2	0.00290
V_3	0.00230
V_4	0.00190

Table 5. Optimized Costs of Energy

Each optimization run has been iterated 50 times for every chosen scenario and transfer function. The plots shown in Fig.5 depict that ‘S’ type transfer functions offer more optimal wind power generation cost when compared to corresponding ‘V’ type transfer functions. Moreover, the ‘S4’ type transfer function, among all the mentioned transfer functions, has presented the minimal CE for every wind flow scenario. The most optimal CE that has been attained in the current WFLO problem is 0.00131 USD/kWh. The accepted error for estimating the CE is less than 0.00001 USD/kWh for the present work [41]-[45].

5. Conclusions

The BPSO-based WFLO methodology presented in the current work has offered an economical and prompt technique to assess the optimum generation cost for a given cost function and five arbitrarily chosen wind flow scenarios taken into account in the 22nd Genetic and Evolutionary Computation Conference [25]. Both types of transfer functions have been considered for changing the particle velocity for BPSO. The research outcomes demonstrate the suitability of S-type transfer functions over V-type ones in finding the optimal wind power generation cost. The ‘S4’ function, mentioned in Table 2, is the most efficient transfer function for exploring the randomly generated layouts to search for the best possible positioning of the WTs inside the wind farm with the most optimal WPG cost per kWh. This study will initiate innovative possibilities for enhancing the plan of the WPG farms to find the least probable CE for several terrains and wind flow conditions using AI methods like the PSO algorithm.

Acknowledgment

The first author admits the pecuniary grant provided by the TEQIP section of Jadavpur University, Kolkata, India to support the present study.

References

[1] Enerdata, "Global Energy Statistical Yearbook," 2020. [Online]. Available: https://yearbook.enerdata.net/

[2] P. K. Chaurasiya, V. Warudkar, and S. Ahmed, "Wind energy development and policy in India: A review," Energy Strategy Reviews, vol. 24, pp. 342-357, 2019. doi: 10.1016/j.esr.2019.04.010.

[3] BP, "Statistical Review of World Energy," 2020. [Online] Available: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

[4] Global Wind Energy Council, "Global Wind Energy Outlook," 2014. [Online] Available: http://www.gwec.net/wp-content/uploads/2014/10/GWEO2014_WEB.pdf

[5] G. Nicholas, T. Howard, H. Long, J. Wheals, and R. S. Dwyer-Joyce, "Measurement of roller load, load variation, and lubrication in a wind turbine gearbox high speed shaft bearing in the field," Tribology International, vol. 148, p. 106322, 2020.

[6] J. S. González, A. G. Gonzalez Rodriguez, J. C. Mora, J. R. Santos, and M. B. Payan, "Optimization of wind farm turbines layout using an evolutive algorithm," Renewable Energy, vol. 35, no. 8, pp. 1671–1681, 2010.

[7] G. Mosetti, C. Poloni, and B. Diviacco, "Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm," Journal of Wind Engineering and Industrial Aerodynamics, vol. 51, no. 1, pp. 105–116, 1994.

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

[9] H. S. Huang, "Distributed Genetic Algorithm for Optimization of Wind Farm Annual Profits," in The 14th International Conference on Intelligent System Applications to Power Systems, Kaohsiung, Taiwan, 2007.

[10] C. N. Elkinton, J. F. Manwell, and J. G. McGowan, "Algorithms for Offshore Wind Farm Layout Optimization," Wind Engineering, vol. 32, no. 1, pp. 67-84, 2008.

[11] A. Emami and P. Noghreh, "New approach on optimization in placement of wind turbines within wind farm by genetic algorithms," Renewable Energy, vol. 35, no. 7, pp. 1559–1564, 2010.

[12] Y. Chen, H. Li, B. He, P. Wang, and K. Jin, "Multi-objective genetic algorithm based innovative wind farm layout optimization method," Energy Conversion and Management, vol. 105, pp. 1318–1327, 2015.

[13] P.-Y. Yin, T.-H. Wu, and P.-Y. Hsu, "Risk management of wind farm micro-siting using an enhanced genetic algorithm with simulation optimization", Renewable Energy, vol. 107, pp. 508–521, 2017.

[14] C. Wan, J. Wang, G. Yang, and X. Zhang, "Particle swarm optimization based on Gaussian mutation and its application to wind farm micro-siting," in 49th IEEE Conference on Decision and Control (CDC), Atlanta, GA, USA, 2010.

[15] S. Chowdhury, J. Zhang, A. Messac, and L. Castillo, "Unrestricted wind farm layout optimization (UWFLO): Investigating key factors influencing the maximum power generation," Renewable Energy, vol. 38, no. 1, pp. 16-30, 2012.

[16] S. Pookpunt and W. Ongsakul, "Optimal placement of wind turbines within wind farm using binary particle swarm optimization with time-varying acceleration coefficients," Renewable Energy, vol. 55, pp. 266–276, 2013.

[17] P. Hou, W. Hu, C. Chen, M. Soltani, and Z. Chen, "Optimization of offshore wind farm layout in restricted zones," Energy, vol. 113, pp. 487-496, 2016.

[18] A. C. Pillai, J. Chick, M. Khorasanchi, S. Barbouchi, and L. Johanning, "Application of an offshore wind farm layout optimization methodology at Middelgrunden wind farm," Ocean Engineering, vol. 139, pp. 287-297, 2017.

[19] A. Duggirala, R. K. Jana, R. V. Shesu, and P. Bhattacharjee, "Design optimization of deep groove ball bearings using crowding distance particle swarm optimization," Sādhanā, vol. 43, no. 1, 2018.

[20] G. Marmidis, S. Lazarou, and E. Pyrgioti, "Optimal placement of wind turbines in a wind park using Monte Carlo simulation," Renewable Energy, vol. 33, no. 7, pp. 1455–1460, 2008.

[21] R. A. Rivas, J. Clausen, K. S. Hansen, and L. E. Jensen, "Solving the Turbine Positioning Problem for Large Offshore Wind Farms by Simulated Annealing," Wind Engineering, vol. 33, no. 3, pp. 287–297, 2009.

[22] B. DuPont, J. Cagan, and P. Moriarty, "An advanced modeling system for optimization of wind farm layout and wind turbine sizing using a multi-level extended pattern search algorithm," Energy, vol. 106, pp. 802–814, 2016.

[23] J. Serrano González, M. Burgos Payán, J. M. R. Santos, and F. González-Longatt, "A review and recent developments in the optimal wind-turbine micro-siting problem," Renewable and Sustainable Energy Reviews, vol. 30, pp. 133-144, 2014.

[24] K. Yang, G. Kwak, K. Cho, and J. Huh, "Wind farm layout optimization for wake effect uniformity," Energy, vol. 183, pp. 983-995, 2019.

[25] D. Wilson, S. Rodrigues, C. Segura, I. Loshchilov, F. Hutter, G. L. Buenfil, A. Kheiri, E. Keedwell, M. Ocampo-Pineda, E. Özcan, S. I. V. Peña, B. Goldman, S. B. Rionda, A. Hernández-Aguirre, K. Veeramachaneni, and S. Cussat-Blanc, "Evolutionary computation for wind farm layout optimization," Renewable Energy, vol. 126, pp. 681-691, 2018.

[26] D. Wilson, S. Cussat-Blanc, S. Rodriguez, and K. Veeramachaneni, "WindFLO," [Online]. Available: https://github.com/d9w/WindFLO/blob/master/Wind%20Competition/2015/slides_GECCO.pdf

[27] M. A. Khanesar, M. Teshnehlab, and M. A. Shoorehdeli, "A novel binary particle swarm optimization," in Mediterranean Conference on Control & Automation, 2007.

[28] J. Liu, Y. Mei, and X. Li, "An Analysis of the Inertia Weight Parameter for Binary Particle Swarm Optimization," IEEE Transactions on Evolutionary Computation, vol. 20, no. 5, pp. 666–681, 2016.

[29] S. Mirjalili, S. M. Hashim, G. Taherzadeh, S. Z. Mirjalili, and S. Salehi, "A Study of Different Transfer Functions for Binary Version of Particle Swarm Optimization," in International Conference on Genetic and Evolutionary Methods, 2011.

[30] S. Saremi, S. Mirjalili, and A. Lewis, “How important is a transfer function in discrete heuristic algorithms,” Neural Computing and Applications, vol. 26, no. 3, pp. 625–640, 2014.

[31] S. Mirjalili, and A. Lewis, “S-shaped versus V-shaped transfer functions for binary Particle Swarm Optimization,” Swarm and Evolutionary Computation, vol. 9, pp. 1–14, 2013.

[32] P. Bhattacharjee, R. K. Jana, and S. Bhattacharya, “A Relative Analysis of Genetic Algorithm and Binary Particle Swarm Optimization for Finding the Optimal Cost of Wind Power Generation in Tirumala Area of India,” ITM Web of Conferences, vol. 40, p. 03016, 2021, doi: 10.1051/itmconf/20214003016.

[33] P. Bhattacharjee, R. K. Jana, and S. Bhattacharya, “Boosting the annual profit of an offshore wind farm in India with a bio-inspired meta-heuristic scheme,” Environmental Challenges, vol. 9, p. 100642, Dec. 2022, doi: 10.1016/j.envc.2022.100642.

[34] P. Bhattacharjee, R. K. Jana, and S. Bhattacharya, “Application of Metaheuristic Techniques for Enhancing the Financial Profitability of Wind Power Generation Systems,” Studies in Computational Intelligence, pp. 127–147, Dec. 2022, doi: 10.1007/978-3-031-16832-1_7.

[35] J. Liu, Y. Mei, and X. Li, “An Analysis of the Inertia Weight Parameter for Binary Particle Swarm Optimization,” IEEE Transactions on Evolutionary Computation, vol. 20, no. 5, pp. 666–681, Oct. 2016, doi: 10.1109/tevc.2015.2503422.

[36] M. Verma, H. K. Ghritlahre, P. K. Chaurasiya, S. Ahmed, and S. Bajpai, “Optimization of wind power plant sizing and placement by the application of multi-objective genetic algorithm (GA) in Madhya Pradesh, India,” Sustainable Computing: Informatics and Systems, vol. 32, p. 100606, Dec. 2021, doi: 10.1016/j.suscom.2021.100606.

[37] S. Rehman and S. S. A. Ali, “Wind farm layout design using modified particle swarm optimization algorithm,” in IREC2015 The Sixth International Renewable Energy Congress, Mar. 2015, doi: 10.1109/irec.2015.7110915.

[38] Z. Liu, J. Peng, X. Hua, and Z. Zhu, “Wind farm optimization considering non-uniformly distributed turbulence intensity,” Sustainable Energy Technologies and Assessments, vol. 43, p. 100970, Feb. 2021, doi: 10.1016/j.seta.2020.100970.

[39] A. G. Conzalez-Rodriguez, J. Serrano-Conzalez, J. M. Riquelme-Santos, M. Burgos-Payán, J. Castro-Mora, and S. A. Persan, "Global Optimization of Wind Farms Using Evolutive Algorithms," Wind Power Systems, pp. 53–104, 2010, doi: 10.1007/978-3-642-13250-6_3.

[40] F. Daqaq, R. Ellaia, M. Ouassaid, H. M. Zawbaa, and S. Kamel, "Enhanced Chaotic Manta Ray Foraging Algorithm for Function Optimization and Optimal Wind Farm Layout Problem," IEEE Access, vol. 10, pp. 78345–78369, 2022, doi: 10.1109/access.2022.3193233.

[41] J. S. Gonzalez, M. B. Payan, and J. M. Riquelme-Santos, "Optimization of Wind Farm Turbine Layout Including Decision Making Under Risk," IEEE Systems Journal, vol. 6, no. 1, pp. 94–102, Mar. 2012, doi: 10.1109/jsyst.2011.2163007.

[42] J.-F. Herbert-Acero, J.-R. Franco-Acevedo, M. Valenzuela-Rendón, and O. Probst-Oleszewski, "Linear Wind Farm Layout Optimization through Computational Intelligence," Lecture Notes in Computer Science, pp. 692–703, 2009, doi: 10.1007/978-3-642-05258-3_61.

[43] M. K. Singla, M. H. Hassan, J. Gupta, F. Jurado, P. Nijhawan, and S. Kamel, "An enhanced efficient optimization algorithm (EINFO) for accurate extraction of proton exchange membrane fuel cell parameters," Soft Computing, Apr. 2023, doi: 10.1007/s00500-023-08092-1.

[44] C. Wan, J. Wang, G. Yang, H. Gu, and X. Zhang, "Wind farm micro-siting by Gaussian particle swarm optimization with local search strategy," Renewable Energy, vol. 48, pp. 276–286, Dec. 2012, doi: 10.1016/j.renene.2012.04.052.

[45] N. Naritsak and K. Asawarungsaengkul, "A Memory Integrated Artificial Bee Colony Algorithm with Local Search for Vehicle Routing Problem with Backhauls and Time Windows," KMUTNB International Journal of Applied Science and Technology, Mar. 2018, doi: 10.14416/j.ijast.2018.03.001.