Mindanao Journal of Science and Technology Vol. 20 (2) (2022) 174-189

Improving the Yearly Profit of Wind Farm with Artificial Intelligence Technique

Prasun Bhattacharjee[1*], Rabin K. Jana[2] and
Somenath Bhattacharya[1]
[1]Department of Mechanical Engineering
Jadavpur University
Kolkata-700032, West Bengal, India
[*]*prasunbhatta@gmail.com*

[2]Operations and Quantitative Methods Area
Indian Institute of Management Raipur
Chhattisgarh, 493661 India

Date received: December 22, 2021
Revision accepted: October 12, 2022

Abstract

Owing to the escalating environmental and social problems linked to climate change and the hastily depleting stock of hydrocarbon-based fuels, renewable power generation modes have attained massive prominence. Wind power is an important renewable energy generation technology that contributed to 5% of the planet's power generation in 2020. However, for sustaining the Paris Agreement targets, the global wind power generation sector necessitates evolving at a fleeter pace. To expand the green switch of the worldwide power generation businesses, wind farms are expected to remain financially more advantageous than fossil fuel-based power plants. The present work focused on elevating the annual profit of wind farms by employing an amended genetic algorithm (GA). A fresh approach to dynamically apportioning the crossover and mutation prospects for a GA-enabled profit growth algorithm was suggested to amplify the capability of the GA. Three dissimilar terrain conditions with diverse obstruction configurations and a randomly generated non-uniform wind flow pattern were used for assessing the competence of the proposed algorithm for profit maximization. The results showed that the annual yields for Terrain Layouts 1, 2 and 3 obtained by the amended GA were higher by 10.34, 5.09 and 0.51%, respectively, than the typical one, which substantiated the superior proficiency of the former.

***Keywords**:* annual profit, artificial intelligence, genetic algorithm, wind power

1. Introduction

The continual discharge of greenhouse gases into the atmosphere because of human actions is responsible for escalating the average surface air temperature and anomalous meteorological conditions triggering worldwide climate change (Obama, 2017). The fragment of renewable energy in inclusive power generation has broadened significantly (Enerdata, 2020). The wind power generation (WPG) area has proceeded firmly in the past 20 years (British Petroleum Company, 2020). Comprehensive WPG competence is expected to reach 4,042 gigawatt (GW) by 2050 (Global Wind Energy Council and Greenpeace International, 2014).

Along with low emission advantages, renewable energy solutions like WPG systems are needed to remain feasible by proposing economical generation costs through superior reliability and minimal cost of maintenance to facilitate the de-carbonization of worldwide energy systems to a greater extent (Nicholas *et al*., 2020). The weighted average of global onshore wind project installed cost per W declined profoundly from 4.88 USD in 1983 to 1.38 USD in 2017 while the auction price of wind power in 2020 to 2022 is expected to be within the range of 0.06 USD/kWh to 0.10 USD/kWh, which is reasonably competitive to fossil fuel cost (International Renewable Energy Agency, 2018).

Internationally, studies have been conducted to lessen the WPG expense and realize the carbon neutrality target proposed in the 2015 Paris Accord (Bhattacharjee *et al*., 2021). Because of the calculating competence, artificial intelligence (AI) has been utilized to resolve different engineering optimization challenges including the WPG outlay minimization problem (Jana and Bhattacharjee, 2017; Duggirala *et al*., 2018; Bhattacharjee *et al*., 2021). A neural network-abetted genetic algorithm (GA) was implemented to foresee WPG outlay (Huang, 2007). GA was employed for wind farm design in Gökçeada Island, Turkey (Şişbot *et al*., 2010). Several possible locations for offshore WPG and their economic practicability were examined (Mani Murali *et al*., 2014). Another study quantified the offshore WPG possibility in India by employing the oceansat-2 scatterometer (OSCAT) orbiter reports (Nagababu *et al*., 2016). Assessment of the offshore WPG capacity and optimization of the generation expenditure in the Indian oceanfront region was accomplished by Singh and Kumar (2018). Wilson *et al*. (2018) applied evolutionary algorithms to curtail the WPG expenditure with different flow scenarios. Wind farm design was improved with vector regression and GA with the premeditation of correlation within land proprietors (Ju *et al*., 2019). A revised most valuable player algorithm was developed by Ramli and Bouchekara (2020) for wind farm design with a minimal generation expense. A large offshore WPG layout for the western seashore of Gujrat state of India was appraised pertaining to the climate study and generation expenditure was assessed (Kumar *et al.*, 2020). In 2021, GA was used in wind farm design accompanied by particle swarm optimization tactics (Roy and Das, 2021).

Although a few AI-backed algorithms have been expended for wind farm design over the years, further innovative reformations of the said algorithms are yet to be investigated for optimization method enhancement. The current study was directed to expand the yearly profit of WPG farms using an amended GA-based optimization approach. GA enhances a binary genome in which every gene signifies the existence or nonexistence of a wind turbine (WT) in every unit of the two-dimensional matrix; hence, both improving the count of WTs and their distinct locations (Wilson *et al*., 2018). Profit expansion of renewable power generation projects is a critical process to boost commercial operability and support the global green progression of power generation enterprises. An advanced amendment for assigning the possibilities of crossover and mutation was aimed to improve the related goal. The solutions attained through the enhanced GA were contrasted with the results achieved by the typical GA with static methods for assigning factors of crossover and mutation for assessing the comparative efficiency.

2. Methodology

2.1 Objective Formulation

In line with the concept of aerodynamics, the kinetic energy generated through a WT was estimated using Equation 1 (Wu and Wang, 2012).

$$P = \frac{1}{2}\rho A\vartheta^3 C_p cos\theta \tag{1}$$

where P denotes the power obtainable for withdrawal by WT; ρ signifies the air density; A represents the swept area; ϑ stands for the airspeed; C_p symbolizes the Betz coefficient; and θ specifies the alignment error (Wu and Wang, 2012; Bhattacharjee *et al*., 2021). The current research was directed to boost the annual profit of wind farms. Maximization of annual profit can support the financial sustainability of the WPG projects. Increased sustainability can help in the green transition of electricity generation businesses. This objective function is more reliable than optimizing the generation expenditure or energy yield separately. To enable global communities to reduce the carbon footprint of conventional thermal power generation units, present-day WPG farms are required to generate the maximum amount of power at an economical generation outlay. The annual profit of wind farms was computed using Equation 2 (Huang, 2007).

$$Maximize\ O = [F - C] \times G \tag{2}$$

where O is the annual profit of the farm; F is the selling price of one unit of electricity; C is the generation cost of one unit of power; and G is the annual generated electricity. The annual profit was calculated in USD while the selling price and WPG cost per unit of wind power were computed in USD/kWh. Annual generated power was calculated in kWh. The WPG cost was calculated following the objective function postulated by Wilson *et al.* (2018). The optimization process involved in the current work was designed to compute the unit generation expenditure and the energy yield simultaneously for a certain WPG farm design. Several randomly generated layout designs were compared parallelly to augment the yearly profit of the farm through AI-enabled methodologies as per Equation 2 after the calculation of the generation outlay and the power output. A randomly generated annual wind-flow form as mentioned in a test case scenario used by Wilson *et al.* (2018) was applied in the current work (Figures 1 and 2).

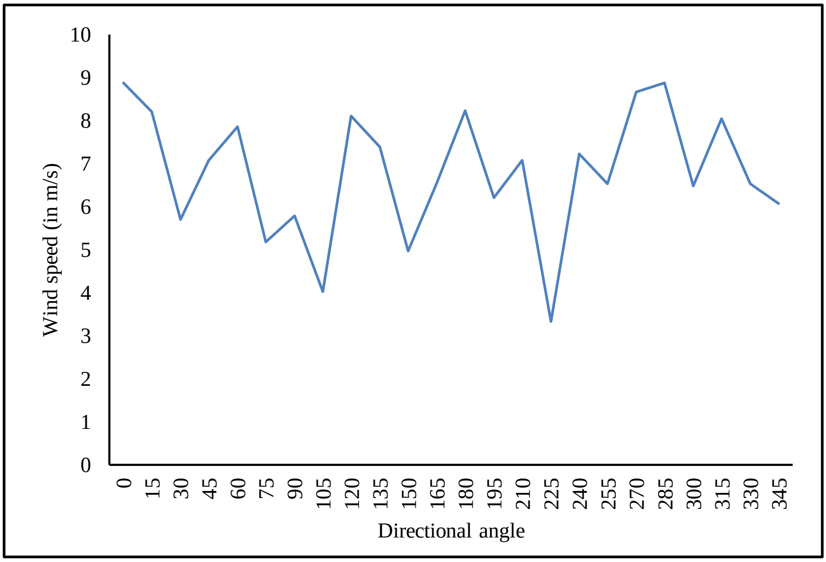

Figure 1. Considered wind flow pattern

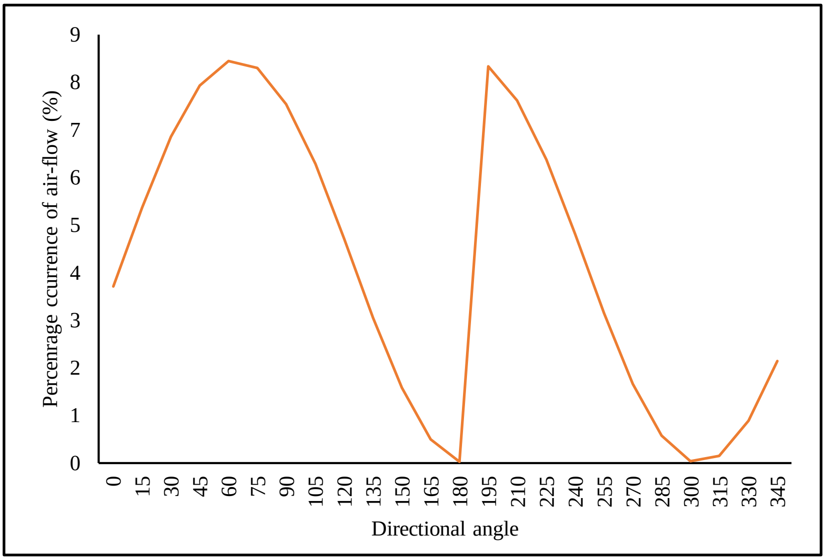

Figure 2. Considered percentage occurrence of wind flow

In Figure 2, the percentage occurrence of wind flow signifies the directional dissemination of airflow over a year and is important in evaluating the estimated annual power generation capacity of any WPG farm. Three dissimilar terrain conditions with different obstacle configurations were considered in the present research to raise the annual profit of the WPG project. The terrain layouts are shown in Figures 3-5.

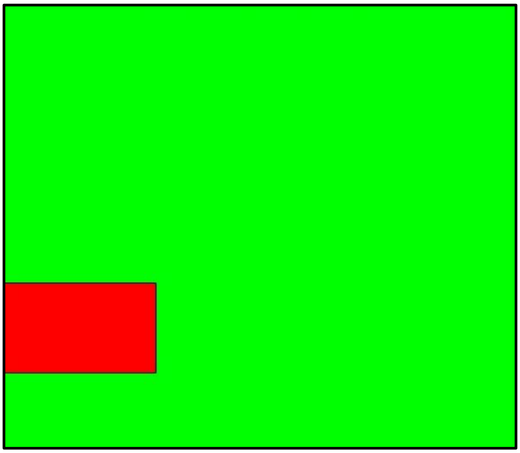

Figure 3. Terrain Layout 1 of 4,000 × 4,000 m with one obstruction of 1,200 × 800 m

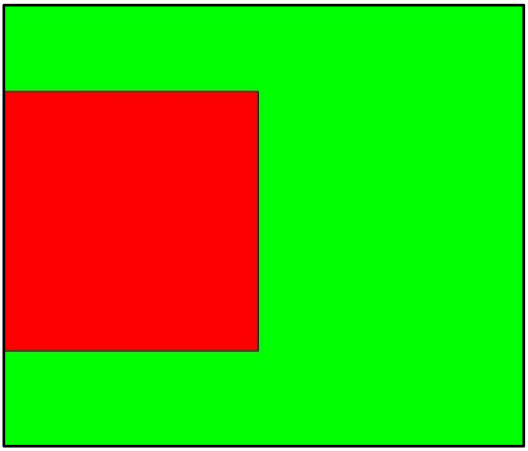

Figure 4. Terrain Layout 2 of 4,500 × 4,500 m with one obstruction of 2,200 × 2,600 m

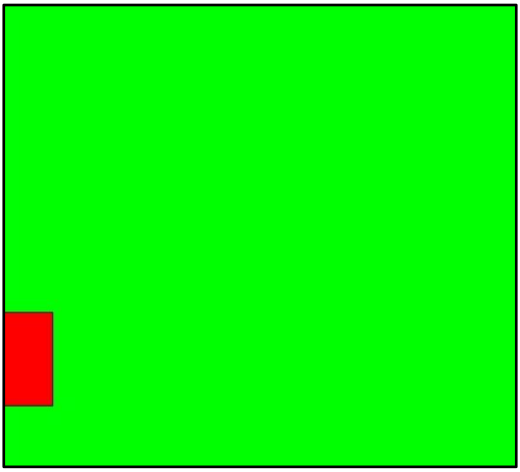

Figure 5. Terrain Layout 3 of 5,000 × 5,000 m with one obstruction of 1,000 × 500 m

The obstacles are marked in red, while the available terrain land for WT placement are highlighted in green. The considered optimization algorithms were designed in such a way that no WT can be placed inside the obstacle area. The deliberation of obstacles enabled the optimization process to address practical issues related to land procurement and other technical difficulties. Three dissimilar layouts with different obstacle sizes were employed to assess the relative efficiency of the proposed optimization approaches with better assurance.

2.2 Proposed Algorithm

GA is a metaheuristic exploring system that advises solutions for optimization work by simulating the development of natural partiality (Turing, 2004). It has been executed in numerous technical branches of learning for solving decision-building problems (Jana and Bhattacharjee, 2017; Abdullah, 2020; Belyaev and Sumenkov, 2021). The essential phases of GA are as follows (Jana and Bhattacharjee, 2017): 1) establishing vital components like population measure, reappearance level, prospects for crossover and mutation procedures; 2) deriving the chromosomes indiscriminately; 3) assessing the fittingness of distinctive components; 4) starting the crossover activity; 5) completing the mutation practice; 6) weighing the relevance of the contemporary entities transformed by crossover and mutation stratagems; and 7) postulating the most enhanced upshot deeming the selection-makers attachment.

In this present optimization scenario, a WPG farm was split into several small-scale cells. Every cell in the WPG farm grid could have only two potential situations: holds a WT (denoted by bit 1) or does not comprise a WT (characterized by bit 0). Thus, for a 20 × 20 matrix, a binary sequence with 400 bits can be formed to characterize the presence of the WTs in the WPG farm. There can be 2^{400} probable situations to assess involving enormous exploration space (Huang, 2007). For the binary chromosome formation ability, GA was employed in the current study with a tournament scale of four for faster and intelligent handling of the optimization process related to the WPG farm design.

In consort with the recognized stratagem of unvarying values, this work exercised a novel dynamical course for appointing the factors of crossover and mutation. For the dynamic approach, the crossover possibility was considered (Equation 3).

$$c_i = \{(c_1 + c_2)/2\} + [\{(c_1 - c_2)/2\}(G_i/G_{max})^6] \tag{3}$$

where c_i denotes the non-linearly mounting crossover chance; c_1 and c_2 are the boundaries of the crossover ratio; G_i is the present reappearance number; and G_{max} is the maximum reappearance number. For the dynamic method, the mutation prospect was computed using Equation 4.

$$m_i = \{(m_1 + m_2)/2\} + [\{(m_1 - m_2)/2\}(G_i/G_{max})^6] \tag{4}$$

where m_i is the non-linearly escalating mutation possibility, and m_1 and m_2 are the confines of the mutation fraction. MATLAB® (R2017a) (MathWorks, 2017) was employed for necessary coding and the execution of the optimization trial of the current WPG farm design enhancement assignment.

3. Results and Discussion

GAs have been utilized several times for WPG farm design owing to their noticeable and acknowledged benchmarks when judged against other AI algorithms. In the present study, GA was applied to determine the possibility of positioning a WT in every single grid of the layout. The focus of the current study was on expanding the yearly profit of a WPG layout. Accompanied by the deliberation of the established stationary tactic, an innovative variable methodology for apportioning the fractions of crossover and mutation procedures of GA-founded WPG farm design optimization tactic. The values of several parameters linked to the deliberated algorithm are presented in Table 1.

Table 1. Values of parameters deliberated for the proposed GA (Wilson *et al*., 2018)

Factor	Deemed value
c_1	0.6
c_2	0.4
m_1	0.05
m_2	0.03
Populace size	20
Extreme recurrence count	50

The descriptions of the WPG farm needed for enhancing the yearly profit of the projected wind farm are shown in Table 2. The wake loss is a prominent aspect of power generation from WT as it reduces the accessible kinetic energy of the wind of the nearby WTs. To curtail the disadvantageous effect of wake loss, a specific space is essential to be sustained amid two nearby WTs for WPG unit design.

Table 2. WT associated parameters (Wilson *et al*., 2018)

Parameter	Deemed value
WT output	1,500 kW
Blade diameter	77 m
Space amid two adjacent WTs	308 m
Least operational wind speed	12 km/h
Highest operational wind speed	72 km/h
Initial purchasing outlay per WT	USD 750,000
Expenditure per sub-station	USD 8,000,000
Yearly operative and repairs charge per WT	USD 20,000
Proportion of interest	3%
Anticipated functioning lifespan	20 years

The stationary values of crossover and mutation fractions were 0.4 and 0.05, respectively. The optimal locations of WTs obtained for three terrain layouts using the varying and static approaches for appointing the crossover and mutation proportions are exhibited in Figures 6-11. The optimal locations of the WTs are shown in red-colored circular dots. The algorithms were designed to place WTs within the bounds of the layouts and not to locate any WT within the obstacle regions.

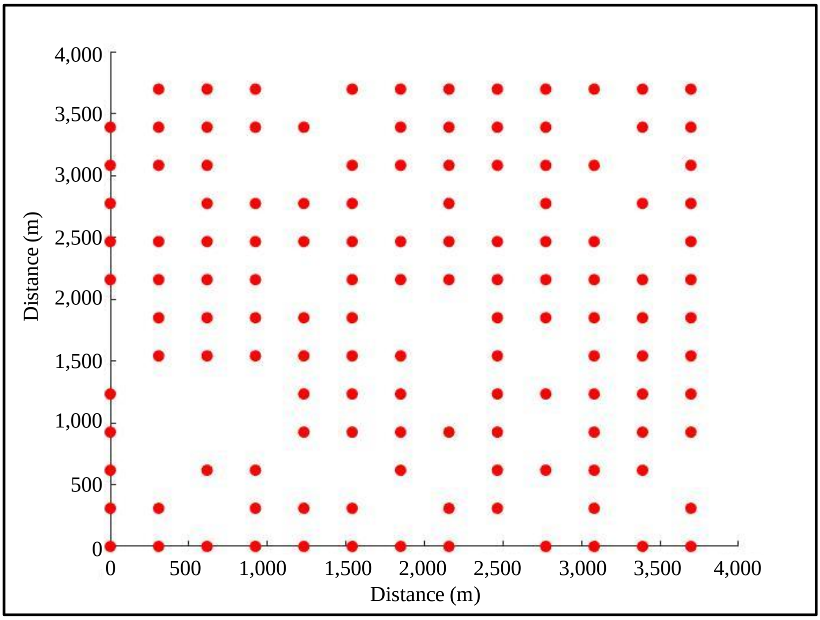

Figure 6. Optimal WPG farm design for Terrain Layout 1 with stationary technique of assigning crossover and mutation probabilities

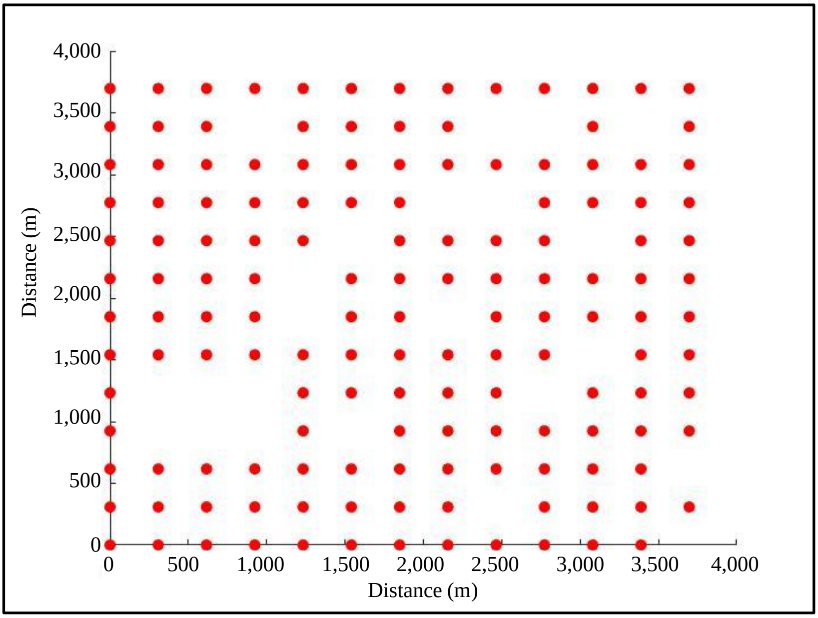

Figure 7. Optimal WPG farm design for Terrain Layout 1 with dynamic process of assigning crossover and mutation probabilities

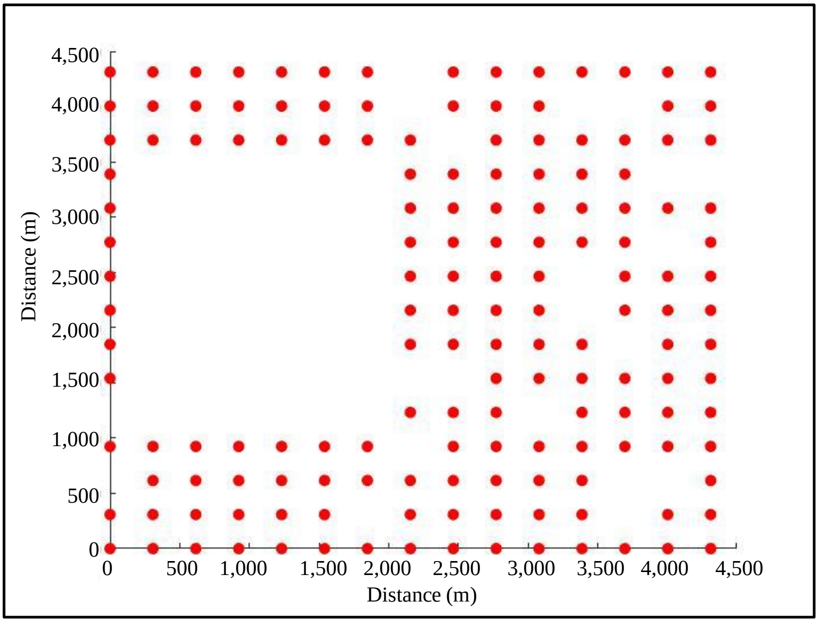

Figure 8. Optimal WPG farm design for Terrain Layout 2 with stationary technique of assigning crossover and mutation probabilities

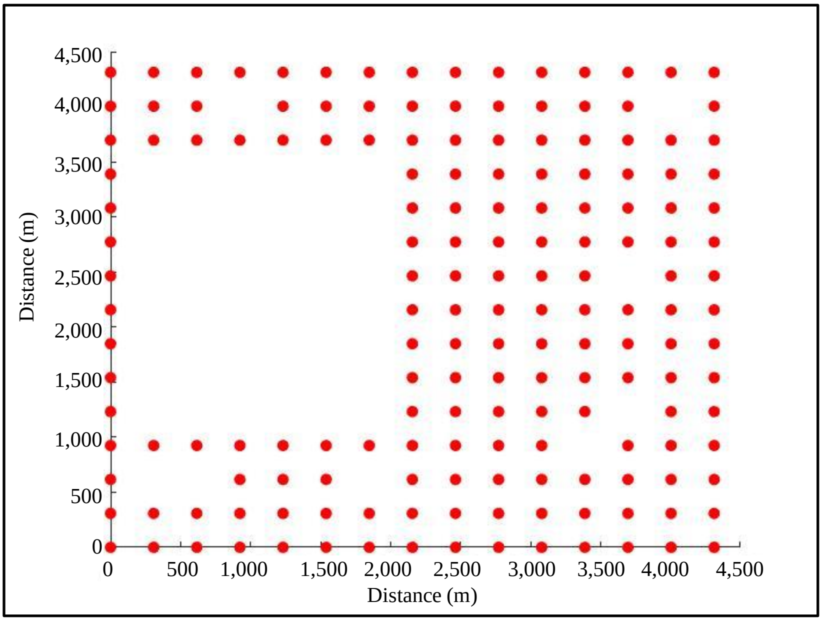

Figure 9. Optimal WPG farm design for Terrain Layout 2 with dynamic process of assigning crossover and mutation probabilities

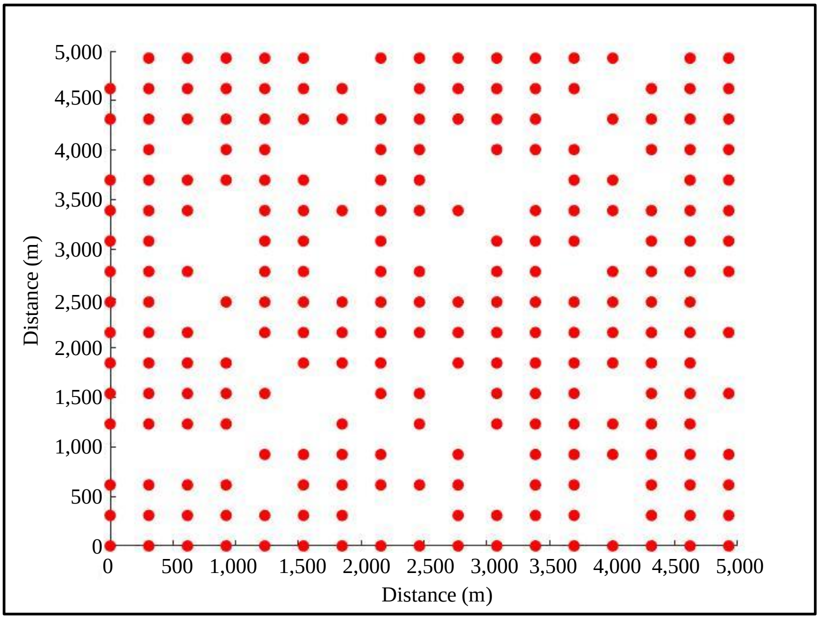

Figure 10. Optimal WPG farm design for Terrain Layout 3 with stationary technique of assigning crossover and mutation probabilities

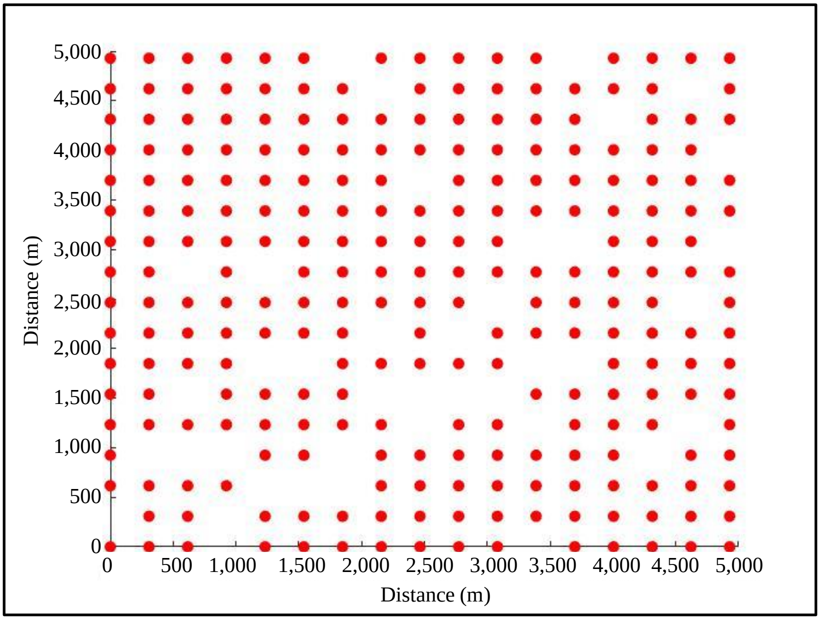

Figure 11. Optimal WPG farm design for Terrain Layout 3 with dynamic process of assigning crossover and mutation probabilities

The graphical representations of the WPG farm design attained by both the optimization approaches display the grid-like structures to maintain the adequate gap required for wake-associated kinetic energy loss minimization. This grid-like design approach would help the concerned decision-makers in obtaining the optimal count of WTs and their locations required for the annual profit maximization for the desired layout setting. An assessment of the optimal annual profits and count of WTs attained through both methods of assigning the potentials of crossover and mutation processes for all the terrain settings is presented in Table 3.

Table 3. Assessment of optimal yearly profit and WT count

Terrain setting	Optimal outcomes attained by GA with static technique of allotting crossover and mutation probabilities		Optimal outcomes attained by GA with dynamic technique of allotting crossover and mutation probabilities	
	Yearly profit (USD)	Count of WT	Yearly profit (USD)	Count of WT
Terrain Layout 1	34,198	132	37,735	146
Terrain Layout 2	42,119	156	44,265	169
Terrain Layout 3	64,810	233	65,145	249

The evaluation results validated the pre-eminence of the projected dynamic method over the standard stationary one in apportioning the probabilities of crossover and mutation for every terrain setting since it achieved a higher annual profit as shown in Table 3. The enlarged cost-effectiveness of the WPG unit would help to increase the convalesced viability of the venture and support the development of emanation management for power generation businesses.

Most of the research performed for the wind farm design optimization procedure focused on generation expenditure curtailment and yearly power generation capacity expansion (Chowdhury *et al*., 2012; Yang *et al*., 2019; Ramli and Bouchekara, 2020; Shin *et al*., 2020). The issue of the financial viability of the wind farm and the appliance of AI for solving such complex computing scenarios need to be studied with more attention to achieve the Paris Agreement targets as early as possible. This inspired the authors of the present study to enhance the annual profit of WPG farms. This work used the time-conditional feature of all constituents of the expenditure and offered a judicious depiction of the WPG industries. Furthermore, the accurate deliberation of flow form in this study affects the more precise computation of the annual profit of the possible WPG farm and influences the effectiveness of the planned AI-assisted optimization technique.

4. Conclusion and Recommendation

This work aimed to raise the annual profit of WPG farms for sustaining the green substitution of electricity generation trades and reaching carbon neutrality goals. A proportional work of standard constant and a proposed dynamic approach for allocating the potentials of crossover and mutation factors for the GA-centered profit development for the wind farm was offered in the existing research. The results confirmed the heightened the appropriateness of the dynamic process over the typical static way for augmenting the wind farm design with supreme yearly profit. The proposed method can sustain the wind power trades in organizing a cost-effective and feasible WPG site with the rational deliberation of numerous expense-allied elements and inconstant airflow circumstances. The existing research can instigate novel potentials for WPG design and the economic possibility of wind power, which can benefit the worldwide attempt to curtail the carbon footprint of the energy generation industries. In the future, more cost functions linked to different geographical and economic conditions can be considered with varied WT-specific parameters for better interpretation of the WPG farm design enhancement process. Moreover, other AI methodologies can be used for comparative analysis of their effectiveness in improving the WPG farm design.

5. Acknowledgement

The first author acknowledges Jadavpur University for supporting this work.

6. References

Abdullah, H. (2020). Milling optimization based on genetic algorithm and conventional method. Journal of Advanced Research in Dynamical and Control Systems, 12(SP7), 1179-1186. https://doi.org/10.5373/jardcs/v12sp7/20202218

Belyaev, A., & Sumenkov, O. (2021). Hybrid control algorithm based on LQR and genetic algorithm for active support weight compensation system. IFAC-Papers OnLine, 54(13), 431-436. https://doi.org/10.1016/j.ifacol.2021.10.486

Bhattacharjee, P., Jana, R., & Bhattacharya, S. (2021). 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, 40, 03016. https://doi.org/10.1051/itmconf/20214003016

British Petroleum Company. (2020). Statistical review of world energy. Retrieved from https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

Chowdhury, S., Zhang, J., Messac, A., & Castillo, L. (2012). Unrestricted wind farm layout optimization (UWFLO): Investigating key factors influencing the maximum power generation. Renewable Energy, 38(1), 16-30. https://doi.org/10.1016/j.renene.2011.06.033

Duggirala, A., Jana, R., Shesu, R., & Bhattacharjee, P. (2018). Design optimization of deep groove ball bearings using crowding distance particle swarm optimization. Sādhanā, 43(1). https://doi.org/10.1007/s12046-017-0775-9

Enerdata. (2020). Global energy statistical yearbook. Retrieved from https://yearbook.enerdata.net/

Global Wind Energy Council and Greenpeace International. (2014). Global wind energy outlook. Retrieved from http://www.gwec.net/wp-content/uploads/2014/10/GWEO2014_WEB.pdf

Huang, H. (2007). Distributed genetic algorithm for optimization of wind farm annual profits. Proceedings of the 14th International Conference on Intelligent System Applications to Power Systems, ISAP 2007, Kaohsiung, Taiwan.

International Renewable Energy Agency. (2018). Renewable power generation costs in 2017. Retrieved from http://www.irena.org/publications/2018/Jan/Renewable-power-generation-costs-in-2017

Jana, R., & Bhattacharjee, P. (2017). A multi-objective genetic algorithm for design optimisation of simple and double harmonic motion cams. International Journal of Design Engineering, 7(2), 77-91. https://doi.org/10.1504/ijde.2017.089639

Ju, X., Liu, F., Wang, L., & Lee, W.-J. (2019). Wind farm layout optimization based on support vector regression guided genetic algorithm with consideration of participation among landowners. Energy Conversion and Management, 196, 1267-1281. https://doi.org/10.1016/j.enconman.2019.06.082

Kumar, R., Stallard, T., & Stansby, P. (2020). Large-scale offshore wind energy installation in northwest India: Assessment of wind resource using Weather Research and Forecasting and levelized cost of energy. Wind Energy, 24(2), 174-192. https://doi.org/10.1002/we.2566

Mani Murali, R., Vidya, P., Modi, P., & Jaya Kumar, S. (2014). Site selection for offshore wind farms along the Indian coast. Indian Journal of Geo-Marine Sciences, 43(7), 1401-1406.

MathWorks. (2017). MATLAB [Computer software]. Natick, Massachusetts: The MathWorks Inc.

Nagababu, G., Simha, R., Naidu, N.K., Kachhwaha, S.S., & Savsani, V. (2016). Application of OSCAT satellite data for offshore wind power. Energy Procedia, 90, 89-98. https://doi.org/10.1016/j.egypro.2016.11.173

Nicholas, G., Howard, T., Long, H., Wheals, J., & Dwyer-Joyce, R. (2020). Measurement of roller load, load variation, and lubrication in a wind turbine gearbox high speed shaft bearing in the field. Tribology International, 148, 106322. https://doi.org/10.1016/j.triboint.2020.106322

Obama, B. (2017). The irreversible momentum of clean energy. Science, 355(6321), 126-129. https://doi.org/10.1126/science.aam6284

Ramli, M., & Bouchekara, H. (2020). Wind farm layout optimization considering obstacles using a binary most valuable player algorithm. IEEE Access, 8, 131553-131564. https://doi.org/10.1109/access.2020.3009046

Roy, C., & Das, D. (2021). A hybrid genetic algorithm (GA)-particle swarm optimization (PSO) algorithm for demand side management in smart grid considering wind power for cost optimization. Sādhanā, 46, 101. https://doi.org/10.1007/s12046-021-01626-z

Shin, J., Baek, S., & Rhee, Y. (2020). Wind farm layout optimization using a metamodel and EA/PSO algorithm in Korea offshore. Energies, 14(1), 146. https://doi.org/10.3390/en14010146

Singh, R., & Kumar, A.S.M. (2018). Estimation of off shore wind power potential and cost optimization of wind farm in Indian coastal region by using GAMS. Proceedings of the 2018 International Conference on Current Trends Towards Converging Technologies (ICCTCT), Coimbatore, India.

Şişbot, S., Turgut, Ö., Tunç, M., & Çamdalı, Ü. (2010). Optimal positioning of wind turbines on Gökçeada using multi-objective genetic algorithm. Wind Energy, 13(4), 297-306. https://doi.org/10.1002/we.339

Turing, A. (2004). Computing machinery and intelligence (1950). In: J. Copeland (Ed.), The essential Turing (pp. 433-464). Oxford, United Kingdom: Oxford University Press.

Wilson, D., Rodrigues, S., Segura, C., Loshchilov, I., Hutter, F., Buenfil, G., Kheiri, A., … Cussat-Blanc, S. (2018). Evolutionary computation for wind farm layout optimization. Renewable Energy, 126, 681-691. https://doi.org/10.1016/j.renene.2018.03.052

Wu, Z., & Wang, H. (2012). Research on active yaw mechanism of small wind turbines. Energy Procedia, 16, 53-57. https://doi.org/10.1016/j.egypro.2012.01.010

Yang, K., Kwak, G., Cho, K., & Huh, J. (2019). Wind farm layout optimization for wake effect uniformity. Energy, 183, 983-995. https://doi.org/10.1016/j.energy.2019.07.019