A novel artificial intelligence technique for enhancing the annual profit of wind farm

Prasun Bhattacharjee[1,*,†], Rabin K. Jana[2,†] and Somenath Bhattacharya[3,†]

[1] Jadavpur University, 188 Raja S.C. Mallick Road, Kolkata 700032, India
[2] Indian Institute of Management Raipur, Sejbahar, Chhattisgarh 492015, India
[3] Jadavpur University, 188 Raja S.C. Mallick Road, Kolkata 700032, India

Abstract

While climate change is triggering off calamitous aftermaths globally, wind energy offers an apposite alternate to conventional fossil fuels for abating greenhouse gas emanations. Economic profitability is an important factor for the green transformation of electricity generation businesses for achieving carbon neutrality as proposed in the Paris agreement of 2015. The current research aspires to expand the annual profit of wind farms employing an adapted genetic algorithm. A dynamic tactic for allotting the crossover and mutation factors has been utilized to quantify their proportional proficiency. A randomly chosen variable wind flow pattern has been employed for calculating the annual profit of wind farms. The research inferences validate the higher competence of escalating mutation and crossover possibilities tactic for expanding the annual profit of wind farms with two arbitrarily selected terrain settings.

Keywords

Annual profit maximization, crossover, genetic algorithm, mutation, wind farm

1. Introduction

The never-ending release of Green House Gases (GHG) into the air is swelling the air temperature and atypical meteorological conditions triggering the macro-climate alteration of the planet[1]. Renewable energy proposes a proliferating alternative amid the ever-increasing international trepidation for the constricted provision of fossil fuels and their perilous penalties on the atmosphere[2]. Astoundingly, the utilization of renewable power inflated by 3% in 2020, even though the requirement of non-renewable fuels collapsed throughout the globe due to pandemic-related restrictions[3].

Accompanied by low GHG production benefit, renewable power solutions like wind energy is necessitated to stay practicable by propositioning inexpensive generation charge through greater consistency and nominal cost of maintenance to expedite de-carbonization of universal energy techniques to a greater degree [4]. The Wind Power Generation (WPG) expense has crashed dramatically over the earlier few decades transnationally[5]. Researchers from every corner of the globe are uninterruptedly endeavoring to boost the profitability of WPG industries to support nations in achieving their carbon neutrality goals as quickly as feasible[6].

Genetic Algorithm (GA) was utilized for wind power generation site design in Gökçeada islet [7]. Saroha and Aggarwal [8] offered a simulation intended for WPG guesstimate with GA and Neural Network (NN). An NN-empowered technique with Particle Swarm Optimization (PSO) and GA has been projected for WPG prognostication [9]. Roy and Das [10] have exercised GA with PSO for WPG expenditure minimization. A proportional study of GA and Binary PSO has been presented to curtail the WPG expenditure [11]. Although most of the studies focused on reducing the WPG charge, more research needs to be aimed at expanding the financial sustainability of wind energy ventures for fulfilling the 2015 Paris agreement commitments made by various governments and global entities.

This research purposes to realize the maximum annual profit of WPG farm for a randomly generated wind flow pattern and two arbitrarily selected layout settings. Because of the intricacy of the WPG process, conventional optimization tactics are inept to manage such conditions. Artificial Intelligence (AI) methods have been previously engaged in miscellaneous technical fields and are apt for the present optimization situation for their heftiness and prompt computing fitness[12, 13, 14, 15, 16].

GA is a prominent AI-aided method emulating the process of organic predilection and ensuing the objective of eminent computer scientist Alan Turing to form a 'knowledge machinery' impending the strategy of genetic

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*Corresponding author.
† These authors contributed equally.
prasunbhatta@gmail.com (P. Bhattacharjee); rkjana1@gmail.com (R. K. Jana); snb_ju@yahoo.com (S. Bhattacharya)
https://www.researchgate.net/profile/Prasun-Bhattacharjee-2 (P. Bhattacharjee); https://www.researchgate.net/profile/Rabin-Jana (R. K. Jana)
0000-0001-9493-5883 (P. Bhattacharjee); 0000-0001-8564-112X (R. K. Jana); 0000-0002-3286-5450 (S. Bhattacharya)

development[17]. GA has been applied in the present research accompanied by a proportional assessment of two distinct procedures of choosing the probabilities of crossover and mutation processes.

2. Problem construction

2.1. Objective function

The power generated by Wind Turbine (WT) can be expressed as follows.

$$P_{WT} = \frac{1}{2}\rho A\vartheta^3 C_p \cos\theta \quad (1)$$

where P_{WT} denotes the generated power, ρ signifies the density of air, A represents the cross-sectional area, v is the speed of the wind, C_p is the Betz threshold value and θ is the angular error of yaw[11, 18]. The current research is dedicated to increasing the annual profit of a WPG farm. The objective function can be formulated as follows.

$$f_A = [S_V - G_C] \times P_{yr} \quad (2)$$

where f_A denotes the yearly profit, S_V signifies the marketing value per unit of wind power, G_C represents the generation price per unit of wind energy and P_{yr} indicates the wind power generated yearly. The generation charge of wind power has been calculated as per the function provided by Wilson *et al.*[19]. The randomly generated airflow has been presented in Fig.1.

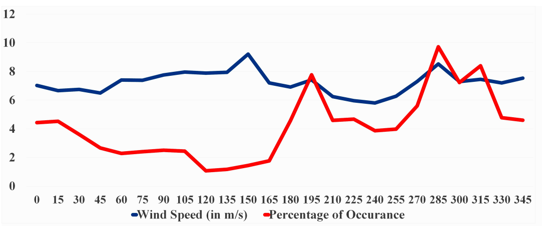

Figure 1: Considered randomly generated wind flow pattern for evaluating the annual profit of wind farm

2.2. Terrain settings

Two arbitrarily selected terrain situations have been selected for evaluating the annual profit of the WPG system. One of the terrains is with no obstacle and another one has an obstacle within it. The presence of obstacles has been considered to evaluate its effect on the profitability of the wind farm and increase the practicability of the simulation. Although the terrain settings selected for the current research are square, they can be easily modified to any rectangular shape as per the need of the decision-makers. The terrain settings have been graphically shown in Figs. 2 and 3.

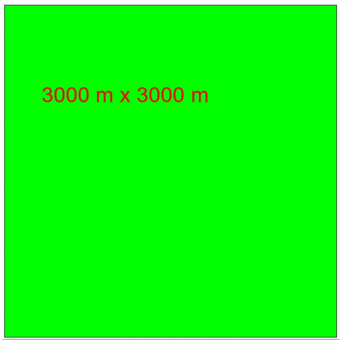

Figure 2: Layout 1 without obstacle

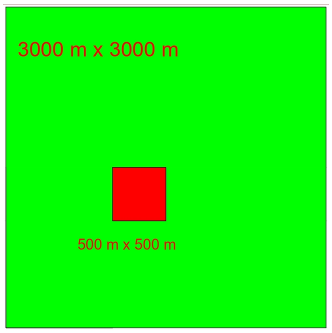

Figure 3: Layout 2 with an obstacle of 500 m x 500 m dimension

3. Optimization algorithm

GA has been employed in the current research to determine the optimal annual profit of the WPG farm for the randomly selected wind flow pattern and two different layout settings. The algorithm has been briefly discussed as follows. GA has been employed in the current research to determine the optimal annual profit of the WPG farm for the randomly selected wind flow pattern and two different layout settings. The algorithm has been briefly discussed as follows[12].

1. Establish the basic factors like populace size, repetition number, probabilities for crossover, and mutation.
2. Organize the populace indiscriminately.
3. Calculate the suitability of all distinct chromosomes.
4. Accomplish the arithmetic crossover technique as follows.

a) Choose a numeral arbitrarily between 0 and 1. If it is less than the chance of the crossover technique, suggest the parental element.
b) Stimulate the crossover activity.
c) Reconsider the relevance of the descendants.
d) If the successor is reasonable, adapt it into the up-to-date populace.

5. Achieve the mutation method as follows.
   a) Elect a numeral arbitrarily between 0 and 1. If it is less than the chance of the mutation tactic, suggest the parental chromosome.
   b) Stimulate the mutation action.
   c) Reconsider the fitness of the mutated units.
   d) If the mutated unit is viable, adapt it into the fresh populace.
6. Measure the appropriateness of the novel units shaped by crossover and mutation methods.
7. Pick the most prominent result understanding the keenness of the choice-maker.

Accompanied by the established system of considering constant values, this research work has applied an innovative dynamic procedure for assigning the factors of crossover and mutation. The dynamic crossover probability has been computed as follows.

$$c_i = c_1 + \left\{ (c_2 - c_1) \left(\frac{R_i}{R_{max}} \right)^{(3/2)} \right\} \quad (3)$$

where c_i is the non-linearly rising crossover possibility. c_1 and c_2 are the bounds of the crossover proportion. R_i is the present recurrence count and R_{max} represents the uppermost reiteration count. The dynamic mutation probability has been calculated as follows.

$$m_i = m_1 + \left\{ (m_2 - m_1) \left(\frac{R_i}{R_{max}} \right)^{(3/2)} \right\} \quad (4)$$

where m_i is the non-linearly growing mutation possibility. m_1 and m_2 are the bounds of the mutation proportion.

4. Results and discussion

GAs have been utilized abundantly in the wind farm designing process. They recommend a noticeable and acknowledged paradigm when contrasted with other optimization processes from the realm of artificial intelligence. The purpose of the existing research is to expand the annual profit of wind farms. The vending charge of wind energy has been considered as USD 0.033/kWh. Accompanied by the deliberation of the standard static method, the current study has considered an innovative non-linearly modifying method for assigning the proportions of crossover and mutation procedures of the GA-based wind farm design process. The values of diverse factors associated with the considered optimization process have been exhibited in Table 1.

Table 1
Values of different factors related to the proposed enhanced GA

Factor	Deemed Value
c_1	0.3
c_2	0.4
m_1	0.04
m_2	0.05
Populace Size	20
Highest Generation Count	50
Static Crossover Factor	0.3
Static Mutation Factor	0.04

The wake forfeiture is a significant feature for power generation from WT as it reduces the accessible kinetic energy of the wind of the in-line WTs. To curtail the disadvantageous outcome of wake damage, a fixed gap is essential to be kept between two in-line WTs for wind farm design. The conditions of the WT have been offered in Table 2.

Table 2
Factors associated to WT

Parameter	Value
Output	1500 W
Blade Radius	38.5 m
Inter-WT Gap	308 m
Minimum Operational Wind Speed	12 km/hr
Maximum Operational Wind Speed	72 km/hr
Capital Expenditure per WT	USD 750,000
Expense per Sub-Station	USD 8,000,000
Yearly Operational Expenditure	USD 20,000
Interest	3%
Probable Life	20 years
WT per Sub-Station	30

The optimal placements of WTs for Layout 1 using the novel dynamic and conventional static approach for allocating the factors of crossover and mutation processes have been shown graphically in Figs. 4 and 5 respectively. This terrain has no obstacle within its boundaries. The possible locations for placing WTs has been marked with circular red marks. The optimal placements of WTs for Layout 2 using the novel dynamic and conventional static approach for allocating the factors of crossover and mutation processes have been shown graphically in Figs. 6 and 7 respectively. This layout has an obstacle of 500 m x 500 m dimension within its terrain. The optimization algorithms have been programmed to avoid placing any WT within the boundaries of the obstacle.

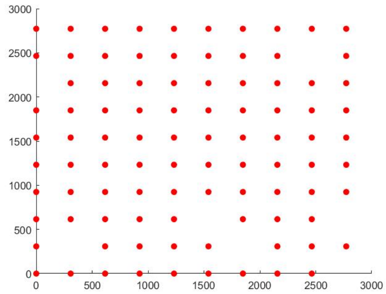

Figure 4: Optimal placement of WTs for layout 1 using the novel dynamic approach for allocating the factors of crossover and mutation processes of GA

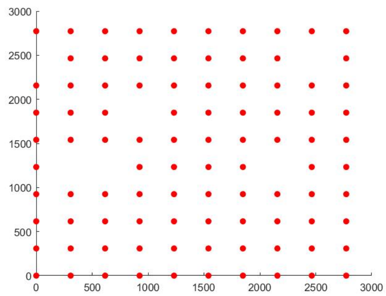

Figure 5: Optimal placement of WTs for layout 1 using the conventional static approach for allocating the factors of crossover and mutation processes of GA

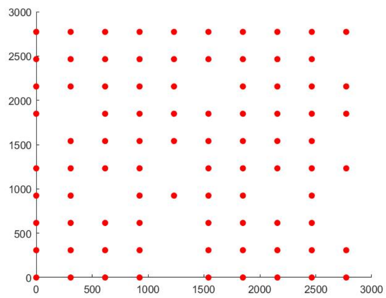

Figure 6: Optimal placement of WTs for layout 2 using the novel dynamic approach for allocating the factors of crossover and mutation processes of GA

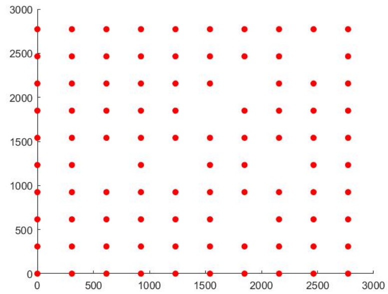

Figure 7: Optimal placement of WTs for layout 2 using the conventional static approach for allocating the factors of crossover and mutation processes of GA

Relative assessments of the optimal yearly profits and quantity of WTs accomplished by all methods of assigning the possibilities of crossover and mutation procedures of GA for both of the terrain designs have been offered in Table 3 and Table 4 respectively.

Table 3
Comparison of optimal yearly profit obtained using both optimization approaches

Optimization Process	Layout 1	Layout 2
Static Approach	USD 22,149	USD 21,845
Novel Dynamic Approach	USD 22,479	USD 22,322

Table 4
Comparison of optimal count of WTs obtained using both optimization approaches

Optimization Process	Layout 1	Layout 2
Static Approach	94	93
Novel Dynamic Approach	93	87

The study results validate the preeminence of the projected novel dynamic approach of assigning crossover and mutation factors over the established static tactic for both designs as it achieved the higher annual profit with lesser WTs as specified in Table 3 and Table 4. The increased cost-effectiveness of the wind farm can allow the enhanced sustainability of the WPG ventures and assist the progression of GHG discharge control for the power generation businesses.

5. Conclusion

Global organizations are continually attempting in the direction of reduction of carbon trails by efficient application of renewable sources like wind power as planned by the Paris treaty of 2015. This study concentrates on amplifying the yearly profit of wind farms through an innovative dynamic approach for allocating the crossover and mutation factors. The optimization results confirm the enhanced suitability of the novel dynamic technique over the typical static method for improving the WPG site designs with the highest yearly profit. The projected method can aid the WPG trades to plan a reasonably feasible wind farm with the realistic deliberation of numerous cost-allied factors and flexible airflow circumstances. The present research can bring about impeccable prospects for wind farm design enhancement and economic sustainability of WPG systems for facilitating the de-carbonization of the global power sector.

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