AN ENHANCED GENETIC ALGORITHM FOR ANNUAL PROFIT MAXIMIZATION OF WIND FARM

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Abstract

Due to the swelling human suffering caused by climate change and the rapidly exhausting reserve of fossil fuels, renewable energy generation processes have gained immense importance throughout the globe. Wind energy is a leading renewable power generation method. To advance the green transition of the electricity generation industry, wind farms should stay commercially sustainable. This paper aims to increase the yearly profit of a wind farm utilizing an enhanced genetic algorithm. A novel method of dynamically allotting the crossover and mutation probabilities has been proposed to increase the effectiveness of the genetic algorithm. The assessment results validate the superior competence of the proposed tactic over the standard invariable method of assigning the crossover and mutation factors.

Keywords: Wind Farm, Profit Maximization, Genetic Algorithm, Dynamic Assignment, Crossover and Mutation Ratios, Annual Profit.

1. Introduction

Renewable power generation techniques recommend a thriving alternate amid the mounting universal disquiet for the constricted hoard of fossil fuels and their hazardous aftermaths on nature. The expenditure of Wind Power Generation (WPG) has fallen dramatically over the previous two decades all over the world. Remarkably, during the Covid-19 associated restrictions in 2020, the utilization of renewable energy underwent an upsurge of 3% whereas the necessity of all fossil fuels plunged across the globe.

The portion of renewable energy in overall energy generation has widened from 19.75% in 1990 to 26.62% in 2019 which is a reasonable indication of the international trend towards low-carbon alternatives of energy resources. Global renewable energy consumption has developed from nearly 941 TWh in 1965 to approximately 7027 TWh in 2019 while the WPG sector has progressed exponentially ever since the preliminary years of the twenty-first century. Global cumulative WPG capacity has expanded from nearly 20 GW in 2000 to 650 GW in 2019 with a forecast of achieving 4042 GW by 2050. Global wind power

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consumption per capita, which was merely 1.89 kWh in 1990, underwent a colossal amplification in the past three decades and reached 458.94 kWh in 2019. Cumulative WPG capacities of nations have been shown in Fig. (1).

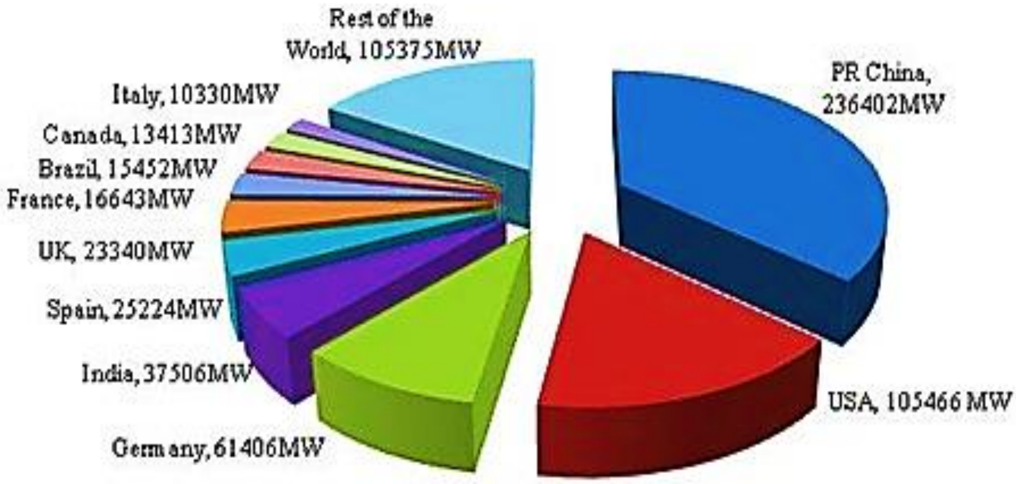

Figure 1: Cumulative Wind Power Generation Capacity as of 2019

Şişbot et al. have engaged Genetic Algorithm (GA) for optimizing the layout of a WPG unit in Gökçeada isle. Saroha and Aggarwal offered a model intended for WPG evaluation with GA and Neural Network (NN). Huang et al. suggested another NN-empowered GA procedure for conjecturing wind power potential. Khosa et al. recommended a profitable dispatch model for probabilistic wind energy generation with GA. Shin and Lee improved the simulation of a generator for WPG through GA. Viet et al. proposed an NN-aided procedure with swarm intelligence and GA for wind power estimating. Roy and Das have utilized GA and swarm intelligence for WPG expenditure minimization. The global trend of WPG project outlay from 1983 to 2017 has been shown in Fig. (2).

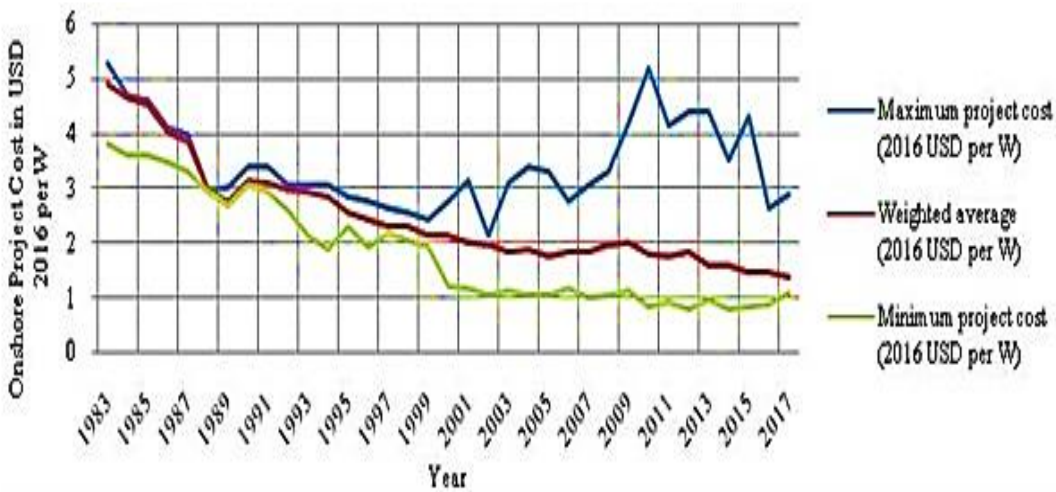

Figure 2: Yearly Statistics of the Global Levelized Cost of Electricity (LCOE) from Onshore WPG System, given in 2016 USD per kilowatt-hour (kWh) from 1983 to 2017

The current study focuses on maximizing the annual profit of a wind farm with an enhanced GA. A novel technique of dynamically allocating the probabilities of crossover and mutation has been proposed and its relative effectivity with respect to the conventional static method of allocating the crossover and mutation ratios has been evaluated.

2. Objective Function

The power captured by a Wind Turbine (WT) is evaluated as per Eq. (1).

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

where P signifies the extricated power, ρ is the density of the current of air, A is the cross-sectional area, v indicates the speed of air, C_p denotes the Betz threshold and θ symbolizes the angular imperfection of the yaw system. The objective function has been defined in Eq. (2).

$$Q = [M - N] \times P_{annual} \quad (2)$$

Where Q denotes the yearly profit, M signifies the marketing charge per unit power, N represents the generation price per unit WPG and P_{annual} indicates the yearly generated power. The current research work deemed the WPG expense function stated by Bhattacharjee et al. (2021) for calculating the annual profit of a wind farm. The wind flow pattern considered in the present study has been shown in Fig. (3).

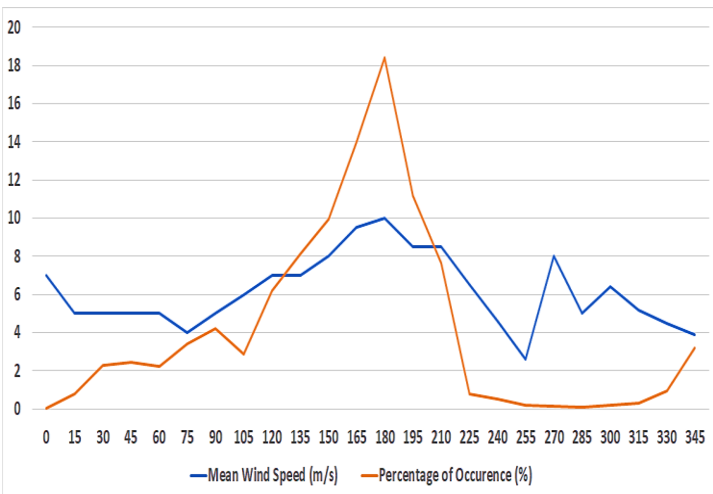

Figure 3. Wind Flow Pattern

3. Proposed Enhanced Genetic Algorithm

GA is an evolutionary exploring method to propose results for optimization study by representing the progression of ecological predilection. It has been implemented in several scientific disciplines for determining choice-building challenges.

The algorithm has succinctly discoursed in the following manner.

1. Establish the essential features like populace extent and recurrence amount.

2. Instigate the population chaotically.

3. Scrutinize the appropriateness of distinctive chromosomes.

4. Assume the crossover process in the subsequent method:

   4.1 Choose a fraction indiscriminately between 0 and 1. If it is not as much of the possibility of the crossover technique, propose the chromosome as the parent unit.

   4.2 Stimulate the crossover activity.

   4.3 Revise the relevance of the descendants.

   4.4 If the inheritor is suitable, adapt it into the fresh population.

5. Accomplish the mutation technique in the succeeding method:

   5.1 Choose a factor unpredictably in the midst of 0 and 1. If it is not as much of the probability of mutation, elect for the unit for the mutation technique.

   5.2 Commence the mutation process.

   5.3 Confirm the recently mutated units for their practicality.

   5.4 Combine the mutated and possible units into the current population.

6. Review the suitability of the fresh units shaped by crossover and mutation approaches.

7. Stipulate the most optimized result concerning the choice-maker's partiality.

For the present study, the dynamic crossover and mutation probabilities have been calculated by Eqs. (3) and (4).

$$c_d = c_1 + \left\{ \left(\frac{c_2 - c_1}{2} \right) \left(\frac{R_c}{R_h} \right)^3 \right\} \tag{3}$$

$$m_d = m_1 + \left\{ \left(\frac{m_2 - m_1}{2} \right) \left(\frac{R_c}{R_h} \right)^3 \right\} \tag{4}$$

Where c_d is the escalating crossover factor. c_1 and c_2 are the bounds of the crossover proportion. m_d is the intensifying mutation factor. m_1 and m_2 are the bounds of the mutation ratio. R_c indicates the current recurrence number and R_h represents the maximum recurrence amount.

The static values of crossover (c) and mutation (m) ratios have been computed as per Eqs. (5) and (6).

$$c = \frac{c_1 + c_2}{2} \tag{5}$$

$$m = \frac{m_1 + m_2}{2} \tag{6}$$

4. Results and Discussions

For the present study, two layouts of sizes of 3000 m x 3000 m and 4000 m x 4000 m have been deemed. c_1 and c_2 have been considered as 0.6 and 0.4 correspondingly. m_1 and m_2 have been deemed as 0.06 and 0.04 respectively.

The extreme number of recurrences has been considered as 50. Population size has been deemed as 20. A 1.5 MW turbine with a radius of 38.5 m has been engaged. For decreasing the wake shortage, the space between two nearby WTs has been maintained as 308 m.

The cost-related variables and their values required for calculating the WPG cost function as described by Bhattacharjee et al. (2021) have been presented in Table 1.

Variable	Considered Value
Turbine Price	USD 750,000
Sub-Station Price	USD 8,000,000 per Sub-Station
Count of Turbines per Sub-Station	30
Percentage of Interest	3%
Yearly Operation and Maintenance Charge	USD 20,000
Probable Operative Lifespan	20 Years

Table 1 Values of WPG Cost Linked Parameters

The minimum and highest operative speeds for WT are 12600 m/hr. and 72000 m/hr. The optimal placements of WTs for 3000 m x 3000 m and 4000 m x 4000 m attained using the conventional static approach of assigning the crossover and mutation ratios have been shown in Figs (4) and (5) respectively.

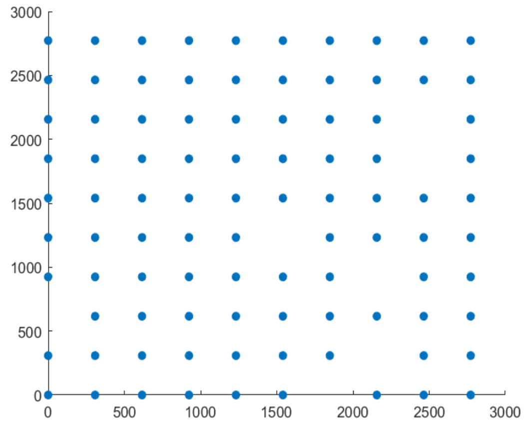

Figure 4. Optimal Placement of Wind Turbines Using Static Approach of Assigning the Crossover and Mutation Ratios for 3000 m x 3000 m Layout

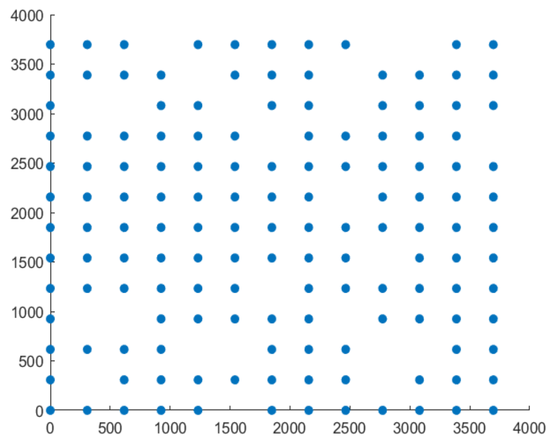

Figure 5. Optimal Placement of Wind Turbines Using Static Approach of Assigning the Crossover and Mutation Ratios for 4000 m x 4000 m Layout

The optimal placements of WTs for 3000 m x 3000 m and 4000 m x 4000 m attained using the proposed approach of dynamically assigning the crossover and mutation ratios have been shown in Figs. (6) and (7) respectively.

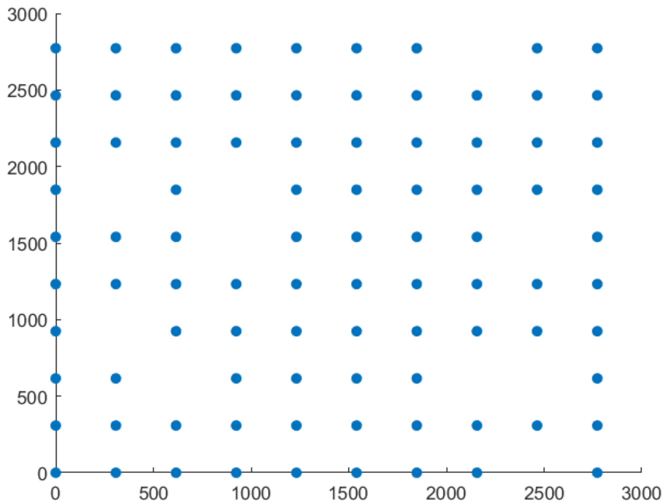

Figure 6. Optimal Placement of Wind Turbines Using Proposed Approach of Dynamic Assignment of the Crossover and Mutation Ratios for 3000 m x 3000 m Layout

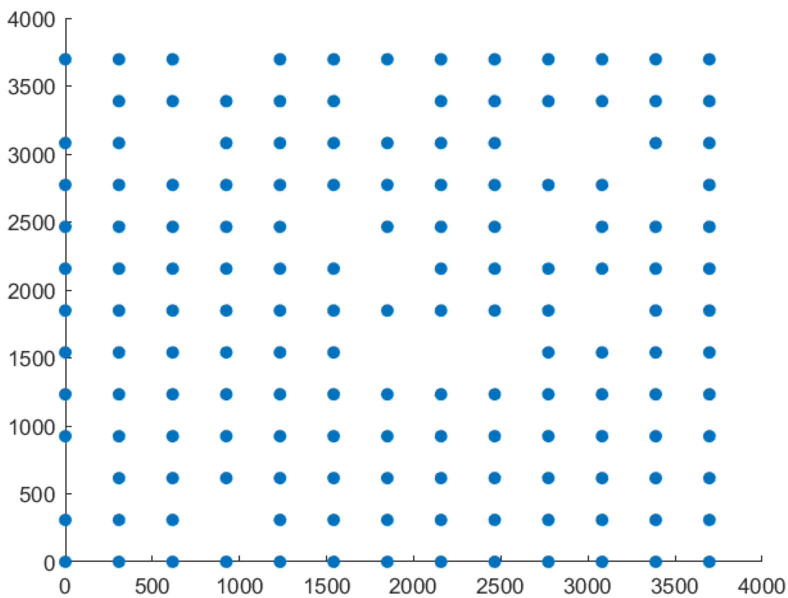

Figure 7. Optimal Placement of Wind Turbines Using Proposed Approach of Dynamic Assignment of the Crossover and Mutation Ratios for 4000 m x 4000 m Layout

The selling price of WPG has been deemed as USD 0.033/kWh. The optimal values of annual profits and corresponding counts of turbine attained by the static and dynamic approaches of allocating the crossover and mutation ratios for both layouts have been presented in Table 2.

Allocation of Crossover and Mutation Ratios	Optimal Yearly Profit for 3000 m x 3000 m Layout (in USD)	Optimal Amount of Wind Turbines for 3000 m x 3000 m Layout	Optimal Yearly Profit for 4000 m x 4000 m Layout (in USD)	Optimal Amount of Wind Turbines for 4000 m x 4000 m Layout
Static Approach	25146	93	42686	145
Proposed Dynamic Approach	25579	90	43571	153

Table 2 Comparison of Optimal Annual Profit and Turbine Count

The study results validate the predominance of the proposed dynamic approach over the standard static approach for both layouts as it realized the highest annual profit as indicated in Table 2. The outcomes prove that the yearly profit of the proposed WPG location upsurges with the augmentation of the amount of WTs for the 3000 m x 3000 m layout. While the yearly profit declines with the augmentation of the amount of WTs for 4000 m x 4000 m layout for enlarged generation expenditure.

The enlarged productivity of the wind farm allows the enhanced sustainability of the WPG ventures and reinforces the progression of emission manipulation for the power generation businesses. The capable location of WTs by the projected optimization approach can benefit the WPG trades to attain elevated fiscal reimbursements without escalating the layout region and evading added outlay in terrestrial possessions.

5. Conclusion

Global societies are continually endeavoring to decrease the carbon footprints by efficient application of renewable resources. Worldwide societies are constantly endeavoring in the direction of diminution of climate change through efficient application of clean energy generation techniques wind energy as projected by the Paris treaty of 2015 and COP-26 of 2021.

The present study aims to maximize the yearly profit of a wind farm. Comparative study of standard static and the projected dynamic tactics for allotting the possibilities of crossover and mutation ratios for the genetic algorithm-based profit expansion of the wind farm. The optimization results confirm the enhanced suitability of the proposed dynamic technique over the usual static method of allocating the crossover and mutation ratios for improving the layouts with the greatest yearly profit.

The present research can initiate fresh opportunities for wind farm layout optimization and financial sustainability of wind farms.

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