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Adam Inspired Dynastic Optimization Algorithm - A fresh look at Wind Turbine Micrositing

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ABSTRACT

This paper introduces AIDOA (Adam Inspired Dynastic Optimization Algorithm), a novel optimization algorithm that combines the exploratory power of dynastic optimization with the adaptive learning rate mechanism inspired by the Adam Optimization Algorithm. We apply AIDOA to the complex problem of wind farm layout optimization, demonstrating its efficacy in finding optimal wind turbine placement in a limited space of 1km by 1 km, the objective function maximizes power output and minimizes the cost. Our results show that the results of the AIDOA are encouraging with respect to the optimal wind farm efficiency and reduction in layout optimization time through a refactored and optimized code.

The AIDOA is adaptive thereby allowing it to populate the complex optimization landscape of wind farm area efficiently, making it a promising tool for renewable energy optimization and beyond.

1. Introduction

Wind energy is one of the most promising renewable energy sources of the world. As wind farms grow in size and complexity, the optimization of turbine layouts becomes increasingly critical for maximizing energy output and minimizing costs. However, wind farm layout optimization presents a challenging problem due to complex wake interactions between turbines, terrain constraints, and the multi-objective nature of balancing power output with installation and maintenance costs as suggested in [1].

Existing optimization techniques often struggle with this problem, either falling into local optima or converging too slowly for practical use. Metaheuristic algorithms like genetic algorithms and particle swarm optimization have shown promise, but often require extensive parameter tuning and can be computationally expensive for large-scale problems.

In this paper, we introduce Adam Inspired Dynastic Optimization Algorithm AIDOA, a novel algorithm that addresses these challenges by combining the global exploration capabilities of dynastic optimization with the efficient, adaptive local search inspired by the Adam optimizer. Dynastic optimization, inspired by the hierarchical structure of royal dynasties, has shown effectiveness in maintaining population diversity and exploring complex solution spaces. The Adam optimizer, widely used in deep learning, provides adaptive learning rates that can efficiently navigate varying gradients in the optimization landscape.

By integrating these approaches, AIDOA aims to provide a robust, efficient method for wind farm layout optimization that can adapt to different problem scales and wind conditions without extensive parameter tuning.

The paper is organized as follows, It starts with the introduction then delves into the materials and methods where it discusses the N.O. Jensen model for calculating the wind turbine wake effects, then it describes the Objective function and its constraints. The DOA is explained next followed by the Adam algorithm. Then the methodology of AIDOA is discussed and the parameters are listed. In the end, the results are discussed and the limitations and conclusions are drawn. The paper concludes in the last section that deals with the summary of the findings and gives the forward directions related to future work and the limitations of the work.

2. Literature Review

A simple model for calculating the wake behind turbines is discussed in [2] and various wake models are discussed in [3], [4] The ethical considerations of implementing new algorithms and processes has been dealt in [5].

A good number of wind farm sites are being inaugurated around the world that require micro siting and sizing up of the wind parameters as mentioned in [6].

The wind farm optimization problem has been discussed in contemporary literature in [7, 8, 9, 10, 11, 12] and particularly in detail in the DOA article [13]. A vast number of optimization algorithms exist for application to this domain such as given in [14, 15, 16, 17, 18]. This problem has been solved in a number of studies [13, 19, 20, 21, 22, 23, 24].

Recent approaches to the Wind Turbine Optimization problem include have been discussed in [25, 26, 27, 28, 29, 30, 31]. A new application of GA has been done in which a complex terrain has been assessed for wind power by utilizing Computational Fluid Dynamics and then a Genetic Algorithm is applied [32]. A new and novel application of the Non-Dominated Sorting Genetic Algorithm (NSGA-III) is made in a complex wind farm scenario that also incorporates optimization of electrical cabling is discussed in [33]. Another novel application of Discrete Particle Swarm Optimization Method is utilized [34] in for calculating the power output of a wind farm. Recently, in another publication, a Elitist Teaching Learning Based Method has been applied to Wind Farm micrositing [35] and [36].

New algorithms such as the Harris Hawks Algorthm [37] have appeared in literature and find a wide applicability. Moreover, a new aerial triangulation modelling approach for wind turbine micrositing is discussed in [38].

Thus, the improvement of the results of the DOA by the application of the Adam optimizer are discussed here that makes reference to these mentioned works.

3. Materials and Methods

3.1 Wind Farm Micrositing using the N.O. Jensen Model

Formulated in 1983 the at the Riso National Laboratory Denmark by N.O. Jensen, this model serves as a computationally cost effective tool for wind farm optimization [9]. It enables the simulation of multiple wake fields by the interaction of multiple turbines cascaded behind each other, on a flat terrain. It is usually advocated that a rotor distance of 5D or about 700 m to 1200 m is sufficient to mitigate the wake effects [39].

The Jensen model has been utilized in [40], [41], [42] as well. For a more detailed study on the wind farm models we may refer to [4]. Here, we take the same assumptions, namely,

wind turbine hub height = 60 m, and

Wind turbine rotor radius = 40 m,

Thrust coefficient = 0.88.

Hence, a graphical layout of the model may be depicted as follows,

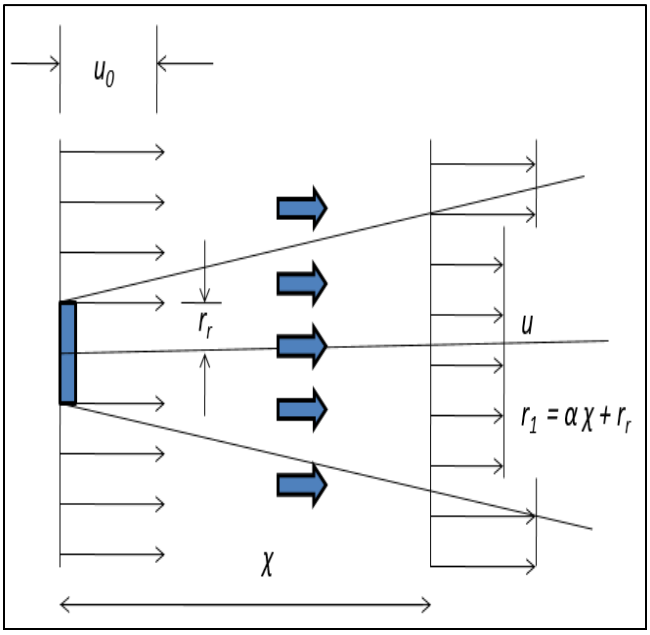

Fig. 1. – The Jensen model illustrating the wake behind the turbine at a distance χ

As depicted, the incident wind velocity u_0, to a wind turbine bearing a rotor radius r_r. Located at some distance χ behind the turbine a the second turbine faces the reduced wind speed. The radius of the wake r_1, may be calculated by the following equation,

$$r_1 = \alpha \chi + r_r \tag{1}$$

This model is based on the central idea that momentum is conserved within the wake radius. It also assumes that the wake propagates in a linear manner downstream from the incident turbine to the next turbine. Hence, by building a cascading turbine model we may sum up the effect of multiple wakes and their resultant interactions. Thus, we may use these values,

r_r = Initial Turbine wake radius

r_1 = Wake radius at when it reaches the second Turbine at a distance of x

χ = The downstream distance at which we calculate the wake radius

Hence, we may derive the wind speed from the Betz's theory as follows,

$$U = u_0 + \left(1 - {2a}/{1 + \alpha \left({x}/{r_1}\right)}\right) \tag{2}$$

Where, U_0 denotes the mean speed of the free stream wind speed. Moreover, a which is the the axial induction factors may be calculated by,

$$C_T = 4\, a\,(1 - a) \tag{3}$$

The turbine radius r_r and the incident radius r_1, at a distance χ, are related to each other by,

$$r_1 = r_r \sqrt[2]{1 - \left({a}/{1 - 2a}\right)} \tag{4}$$

Whereas, the entertainment constant, a, may be derived by,

$$\alpha = {0.5}/{\ln\left({z}/{z_0}\right)} \tag{5}$$

Where,

z = Height of the Wind Turbine Hub

z_0 = Roughness of the Terrain = 0.3 (for flat areas)

Hence, we may derive the equation for wind turbines, using the Jensen Model, having multiple wakes as,

$$u = u_0 \left[1 - \sqrt{\sum_{i=1}^{N_t} \left(1 - {u_i}/{u_0}\right)^2}\right] \tag{6}$$

Where,

N_t = Incident wake Turbines (Total Number)

u_0 = Incident wind speed,

u_i = i^th turbine wind speed,

u = resultant wind speed at i^th wind turbine

Therefore, it is important to lay the turbines in a manner by which each wind turbine gets a maximum amount of inertia.

Hence, the Available Power is given by,

$$\text{Available Power} = \frac{1}{2}\, \rho\, A\, u^3 \tag{7}$$

If we multiply the efficiency of the turbine in this equation, we have,

$$\text{Available Power} = \eta \frac{1}{2}\, \rho\, A\, u^3 \tag{8}$$

The maximum power produced may be derived as follows,

$$\text{Power Produced} = 0.3u^3 \text{ Kilowatts} \tag{9}$$

The efficiency, η, is assumed from literature particularly from [43] to calculate the efficiency of the rotor. Hence, assuming that the maximum power coefficient is 0.59 as per recommendation in [43]. From the Betz limit we have,

$$\eta = {\left(\sum_{i=1}^{Nt} 0.59 \times u_i^3\right)}/{N_t\left(0.59 \times u_i^3\right)} \tag{10}$$

Hence,

$$\eta = {\text{Power}_{Total}}/{N_t\left(0.59 \times u_0^3\right)} \tag{11}$$

A dimensionless cost model is used in this study and it predicts reduction in cost by one third by the installation of every new turbine as follows,

$$Cost = N_t\left({2}/{3} + {e^{-0.00174 * N_t^2}}/{3}\right) \tag{12}$$

3.2 Objective Function

To evaluate the proposed AIDOA (Adaptive Dynastic-Descent Optimization) algorithm, we formulated the wind farm layout optimization as a constrained, single-objective problem. The goal was to maximize the efficiency of turbine placement within a defined wind farm area, by optimizing the trade-off between total power output and total cost. The optimization objective is defined as:

$$Maximise{:}\, f(X) = \frac{P(X)}{C(X)} \tag{13}$$

where:

X is a vector of turbine positions $[x_1, y_1, x_2, y_2, \ldots, x_n, y_n]$

P(X) denotes the total power output of the wind farm

C(X) is a dimensionless vector of the cost of installation and maintenance of the wind farm.

3.2.1 Constraints

Minimum Turbine Distance: A minimum spacing of 5 rotor diameters was required to mainly overcome wake losses and any safety requirements.

Boundary Constraints: All turbine placements were made in 2 km × 2 km rectangular area.

Terrain Constraints: It was assumed that the wind farm consists of a Flat terrain. Future work shall include multi-height turbines, elevations in terrain etc.

Wake Model: The Jensen wake model was selected due to its simplicity and accuracy.

3.3 The Dynastic Optimization Algorithm

This algorithm generates and evaluates a random population,

$$Np = \{1, 2, 3....m\} \tag{14}$$

$$\forall m \in I, N_r \subseteq N_p,$$

$$N_w \subseteq N_p \; N_w \subseteq N_p$$

Thus, for an objective function,

$$F(x) \text{ where } x = (x_1, x_2, x_3, x_4....x_m) \tag{15}$$

A fixed ratio of the population, r_r shall be ranked as rulers and their positions will be fixed. Another fixed ratio of the population shall be taken as workers and shall be generated in the vicinity of the rulers in a fixed radius. The remaining ratio of the population shall be taken as Explorers and shall be randomly generated in the search space. The total of ratio of the three types, rulers, workers and explorers should be unity.

$$r_r = 0.5,\ r_w=0.55 \text{ and } r_e=0.4 \tag{16}$$

$N_r=r_r*N_p \;\; \forall N_r \in I$ and so on

At the end of every iteration, the three types shall be ranked and the rulers separated from the population,

Rank (N_r) =

$$\max \{|N_p| \;\; N_r \subseteq N_p, \forall N_r = 0.2 * N_p\} \text{ and so on} \tag{17}$$

The position of the Rulers shall be fixed while the workers shall be generated in a radius around the closest rulers,

$$rad_w = 0.4 \text{ ss} \quad \forall rad_w \leq 1 \tag{18}$$

Ss is the search space

The Euclidean distance shall govern the distance between the rulers and the workers,

$$\text{Distance} = \sqrt{|x_{r,i}|^2 - |x_{w,j}|^2} \tag{19}$$

where, r = Rulers and w = Workers and i,j $\subseteq$ I

While the explorers are randomly generated and allowed to move in the unexplored space randomly,

$$x_w = rand(x_i) \forall i \in I \tag{20}$$

The whole population shall be ranked and the rulers shall again be selected and the process is repeated for every iteration

After reaching the requisite, number of iterations the algorithm will return the best ruler or the emperor as the best solution [44].

$$x_{best} = \max F(x) \tag{21}$$

3.4 The Adam Optimizer

3.4.1 Introduction

The Adam Algorithm, or Adaptive Moment Estimation Algorithm, is a first order gradient-based algorithm for optimizing stochastic objective functions. It is primarily based on adaptive estimates of moments of lower order in an objective function [45].

This algorithm is computationally cost effective, straight forward as it is less memory intensive and tolerant of diagonal rescaling within the gradients. It is well suited for this NP Hard problem. The Adam Algorithm has proven its efficacy in noisy and sparse gradients having non-stationary objectives. The hyper-parameters require less tuning and converge without much tuning. The algorithm has a mathematically proven convergence rate in the convex optimization framework.

This method is derived from the gradient descent type of optimization algorithm and in this method the computation of the first order partial derivatives as related to the parameters has a similar complexity in all cases. The Objective function is derived from a set of iterations and optimization may be efficiently applied through gradient steps. Since, Adam has proven its worth in many machine language applications and is deemed to be useful for this application.

Adam optimizer requires only first order gradients with minimal memory requirements. It involves adaptive learning rates as derived from the estimates of the first and second moments of the gradients. Obvious advantages of Adam being that the magnitude of parameter variance do not affect the rescaling of the gradient. Moreover, it caters for a dynamic objective and performs step size annealing type of optimization.

Adam versatility may be attributed to its easily scalable implementation to large scale machine learning problems.

3.4.2 Algorithm

Assuming that we have an objective function f(θ) that is noisy, scalar and differentiable with respect to the parameter θ. We want to minimize the expected value of the function, $\mathbb{E}$ [f(X)], With respect to the parameter θ. With the subsequent timesteps (1,2,3,….T) we have the following realizations of the function, $f_1(X)$, $f_2(X)$, $f_3(X)$, …. $f_T(X)$.

The stochasity of the above function may arise from the different evaluations being simulated. Hence, we may denote a gradient,

$$g_t = \nabla_t f_t(X), \tag{22}$$

of a series of partial derivatives of f_T, evaluated with respect to X, at timesteps T.

Where the, gradient is (mt) and the squared gradient is (vt) that is updated by the algorithm. The hyper-parameters being,

$$\beta_1, \beta_2 \in [0, 1) \tag{23}$$

These hyper-parameters are updated with respect to the exponential moving averages of the gradient and the squared gradient. These moving averages are the estimates of the mean (1st moment) and the variance (2nd moment) of the gradient. These moving averages initialize slowly from their 0 average position as the algorithm is run. Allowance for bias correction is possible in these moving averages.

It is also possible to increase the efficacy of the algorithm by replacing the last three lines as follows,

$$\alpha_T = {\alpha\sqrt{1-\beta_2^t}} \Big/ {(1-\beta_1^T)} \tag{24}$$

And,

$$\theta_t \leftarrow \theta_{t-1} - {\alpha . m_t} \Big/ {(\sqrt{v_t} + \varepsilon)} \tag{25}$$

3.5 AIDOA Algorithm Implementation

AIDOA integrates two core optimization paradigms: the hierarchical, population-based structure of Dynastic Optimization and the adaptive, gradient-informed learning of the Adam optimizer. The algorithm maintains a dynamically evolving population segmented into rulers, followers, and explorers, each serving specific roles in exploration and exploitation of the search space.

This hybrid nature of The AIDOA algorithm ensures that DOA guides the population structure with rulers, followers, and explorers. While Adam adaptively tunes the follower radius based on cost improvement gradients, enhancing convergence. The adaptive follower radius updates per iter iteration using Adam momentum and RMS estimates, enabling a learning-rate-inspired step size that adjusts according to progress. Each decision variable i.e. the turbine coordinate is adapted independently using first and second-order moment estimates of directional improvements. A Temporal trade-off control ensures that a linearly decreasing factor governs the balance between exploration (randomized explorer generation) and exploitation (refined follower updates near elite rulers).

The Adam (Adaptive Moment Estimation) algorithm is primarily used for training deep learning models for optimization. It combines the benefits of two other popular methods, namely,

1) Momentum (which accelerates gradients in the right direction), and
2) RMSProp (which adapts learning rates for each parameter)

Adam works well with sparse gradients, noisy data and is particularly useful in handling large datasets and complex architectures of Convolutional Neural Nets and Recurrent Neural Networks alike.

Adam performs its work by maintaining two moving averages,

1) First moment estimate (mean of gradients such as the Momentum) and the
2) Second moment estimate (uncentered variance such as the RMSProp)

It then bias-corrects these moving averages to ensure stability, especially in early iterations. The algorithm adapts learning rates for individual parameters, improving both convergence and generalization.

The Adam optimizer is a go-to choice in modern deep learning due to its, Adaptability to sparse gradients, fast convergence and Robustness to noisy data.

It brings together the strengths of momentum-based and adaptive learning rate methods into a single powerful technique and requires a minimal tuning.

Hence, with both algorithms working in tandem we may summarize that the AIDOA,

1. Initializes population of candidate layouts,
2. At each generation,
3. Evaluates fitness of each individual,
4. Selects top individuals as rulers,
5. Around each ruler,
6. Computes adaptive step sizes using Adam rules,
7. Generates followers using this radius,
8. Adds a set of randomly initialized explorers,

9. Updates population with new rulers, followers, and explorers
10. Repeats until maximum number of generations are reached

The AIDOA algorithm was implemented in MATLAB R2017b.

3.6 Computational Setup and Evaluation Metrics

All simulations were conducted on an intel Core i7, 7th Generation machine with CPU @ 2.7 ~ 2.9 Ghz, 16 GB RAM. Algorithm run was initialized at the beginning of the simulation, for 1 to 100 turbines, The Matlab code runs a pseudo-random code for seeding the initial algorithm run.

The performance of AIDOA was evaluated based on its parameter of Best Fitness achieved by the ruling population as evident from the Power to cost ratio attained.

3.7 Parameters Selected

3.7.1 Parameters of the DOA

The following parameters of the Dynastic Optimization Algorithm were selected in this study,

Parameters of DOA	Value
max_turbines	100
turbine_step	1
wind_speed	12
farm_size	2000
turbine_radius	27.881
wake_decay	0.09437
max_power_coefficient	0.59
base_cost	2/3
variable_cost	1/3
cost_factor	-0.00174
population_size	100
max_generations	100
ruler_ratio	0.05
follower_ratio	0.55
explorer_ratio	0.4
follower_radius	0.3
A	0.326795

3.7.2 Parameters of the Adam Algorithm

The following Adam algorithm parameters were used in conjunction with the Dynastic Optimization Algorithm,

Parameters of Adam	Value
M	1
V	2
beta1	0.99
beta2	0.9999
Epsilon	1e-8

4. Results and Discussion

4.0.1 Description

The below parameters pertain to the power, cost, efficiency and Annual Energy Production (AEP) calculations of the wind turbines placed in the open area.

4.1 Comparison of Power

A comparison of the results of power obtained by GA, DOA and AIDOA

No of Turbines	Power by GA	Power by DOA	Power by AIDOA
1	518.4	518.4	1019.52
2	1,036.80	1,036.80	2,039.04
3	1,555.20	1,555.20	3,058.56
4	2,073.60	2,073.60	4,078.08
5	2,592.00	2,592.00	5,097.60
6	3,110.40	3,110.40	6,117.12
7	3,628.80	3,628.80	7,136.64
8	4,147.20	4,147.20	8,156.16
9	4665.6	4,665.60	9175.68
10	5,184.00	5,184.00	10,195.20
11	5,702.40	5,702.40	11,214.72
12	6,220.80	6,220.80	12,234.24
13	6,739.20	6,739.20	13,253.76
14	7,257.60	7,257.60	14,273.28
15	7,776.00	7,776.00	15,211.72
16	8,294.40	8,294.40	16,199.16
17	8812.8	8,812.80	17181.1234
18	9,331.20	9,328.22	18,090.04
19	9,849.60	9,845.28	19,059.82
20	10,351.68	10,359.23	20,035.33
21	10,853.76	10,880.17	20,756.18
22	11,355.84	11,394.89	21,664.14
23	11,857.92	11,909.58	22,707.21
24	12,360.00	12,429.13	23,610.34
25	12862.08	12,805.65	24235.8215
26	13,364.16	13,453.78	25,477.57
27	13,866.24	13,969.90	26,065.90
28	14,368.32	14,485.15	27,159.13
29	14,870.41	14,996.40	27,948.08
30	15,372.49	15,514.40	28,661.30
31	15,874.57	16,027.31	29,497.83
32	16,376.65	16,559.21	30,372.62
33	16878.73	17,053.30	30969.0787
34	17,380.81	17,562.23	31,687.14
35	17,882.89	18,066.46	32,349.61
36	18,384.97	18,573.76	33,253.89
37	18,887.05	19,097.40	34,314.06
38	19,389.13	19,596.40	34,615.19
39	19,875.40	20,131.35	36,120.57
40	20,361.68	20,640.35	35,869.58
41	20847.95	21,144.41	37046.3863

42	21,334.23	21,664.12	37,309.60
43	21,820.50	22,179.64	39,329.65
44	22,306.78	22,666.38	39,792.09
45	22,793.05	23,181.67	39,559.96
46	23,279.33	23,667.78	40,118.76
47	23,765.60	24,178.36	41,296.93
48	24,251.87	24,685.19	42,478.93
49	24738.15	25,194.62	42055.2868
50	25,224.42	25,697.39	43,287.42
51	25,710.70	26,203.16	43,775.52
52	26,196.97	26,719.00	44,854.99
53	26,683.25	27,210.82	45,187.81
54	27,169.52	27,748.88	45,616.59
55	27,655.80	28,193.69	46,142.36
56	28,142.07	28,753.09	47,066.29
57	28628.34	29,130.48	48093.1089
58	29,099.31	29,687.59	48,931.67
59	29,570.28	30,242.16	48,362.98
60	30,041.24	30,741.34	49,089.00
61	30,512.21	31,278.57	50,170.04
62	30,983.17	31,640.64	50,438.60
63	31,454.14	32,200.11	50,366.13
64	31,925.11	32,642.62	50,979.62
65	32396.07	33,123.50	52123.5675
66	32,867.04	33,632.55	52,979.17
67	33,338.00	34,173.13	53,351.74
68	33,808.97	34,195.85	53,793.17
69	34,279.94	35,102.20	53,730.09
70	34,750.90	35,651.06	53,969.30
71	35,221.87	36,224.84	55,926.04
72	35,692.83	36,637.20	55,963.51
73	36163.8	37,072.03	57969.68
74	36,634.76	37,613.83	58,375.07
75	37,105.73	38,080.59	57,552.51
76	37,576.70	38,671.75	58,241.11
77	38,032.84	39,084.93	59,339.42
78	38,488.98	39,661.54	59,318.53
79	38,945.12	39,516.82	59,141.63
80	39,401.26	40,750.09	59,784.34
81	39857.4	41,107.04	61631.904
82	40,313.54	41,465.55	60,777.35
83	40,769.68	42,185.95	61,095.16
84	41,225.82	42,506.64	62,041.97
85	41,681.96	43,123.26	62,931.99
86	42,138.10	43,316.21	61,642.92
87	42,594.24	43,863.89	63,858.72
88	43,050.38	44,328.75	64,865.87
89	43506.51	44,977.38	64728.5356
90	43,962.65	45,593.26	64,755.85
91	44,418.79	45,646.31	65,680.56
92	44,874.93	46,039.29	65,624.58
93	45,331.07	46,885.14	66,479.28
94	45,787.21	47,024.66	65,095.40
95	46,243.35	47,563.55	66,763.88
96	46,685.14	48,202.02	66,808.01
97	47126.92	48,753.12	67429.8418
98	47,568.70	48,430.18	67,569.10
99	48,010.48	49,256.42	69,295.69
100	48,452.26	49,831.45	69,550.10

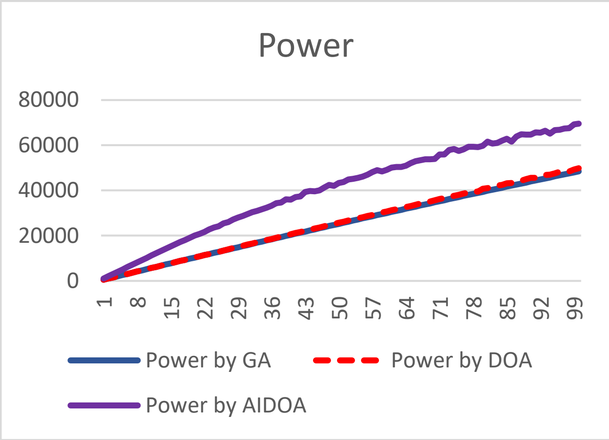

Fig. 4.1. A comparison of Power obtained by GA, DOA and AIDOA

The above power graphs show that the power produced by AIDOA is higher thatn the DOA and the GA.

4.2 Comparison of Cost

A comparison of the results of cost incurred by GA, DOA and AIDOA

No of Turbines	Cost by GA	Cost by DOA	Cost by AIDOA
1	0.0019279	0.00192789	0.9994205
2	0.0019246	0.00192455	1.99537611
3	0.001919	0.00191902	2.98446198
4	0.0019114	0.00191136	3.96339195
5	0.0019016	0.00190164	4.92905426
6	0.00189	0.00188997	5.87856311
7	0.0018765	0.00187646	6.80930484
8	0.0018613	0.00186125	7.71897768
9	0.0018445	0.00184448	8.60562427
10	0.0018263	0.00182632	9.46765633
11	0.0018069	0.00180694	10.303871
12	0.0017865	0.0017865	11.1134591
13	0.0017652	0.0017652	11.8960044
14	0.0017432	0.0017432	12.6514755
15	0.0017207	0.00172071	13.3802103
16	0.0016979	0.00169788	14.0828927
17	0.0016749	0.0016749	14.7605246
18	0.0016519	0.00165245	15.4143921
19	0.0016291	0.00162982	16.0460278
20	0.0016091	0.00160796	16.6571708
21	0.0015893	0.00158543	17.2497243
22	0.0015697	0.00156436	17.8257129
23	0.0015506	0.0015439	18.3872409
24	0.0015321	0.00152355	18.9364505
25	0.0015142	0.00152085	19.4754841
26	0.001497	0.00148705	20.0064478

27	0.0014807	0.00146969	20.5313799
28	0.0014652	0.00145337	21.0522227
29	0.0014506	0.0014384	21.5707984
30	0.0014369	0.00142376	22.0887903
31	0.0014241	0.00141057	22.607728
32	0.0014123	0.00139674	23.1289771
33	0.0014014	0.00138705	23.6537332
34	0.0013914	0.00137699	24.1830199
35	0.0013822	0.00136815	24.7176903
36	0.0013739	0.0013599	25.2584322
37	0.0013663	0.00135127	25.8057748
38	0.0013595	0.00134515	26.3600991
39	0.0013545	0.0013373	26.9216492
40	0.0013501	0.00133188	27.4905447
41	0.0013463	0.00132739	28.0667948
42	0.0013429	0.00132248	28.6503122
43	0.0013401	0.00131837	29.2409272
44	0.0013376	0.00131642	29.8384011
45	0.0013356	0.00131321	30.4424403
46	0.0013339	0.00131202	31.052708
47	0.0013325	0.0013098	31.6688362
48	0.0013315	0.00130809	32.2904362
49	0.0013306	0.00130651	32.9171076
50	0.00133	0.00130552	33.5484469
51	0.0013296	0.00130458	34.1840539
52	0.0013293	0.00130332	34.8235381
53	0.0013292	0.0013034	35.4665231
54	0.0013292	0.00130141	36.1126502
55	0.0013293	0.00130389	36.7615811
56	0.0013294	0.00130118	37.4130003
57	0.0013297	0.00130676	38.0666153
58	0.0013307	0.00130432	38.722158
59	0.0013317	0.00130214	39.3793839
60	0.0013328	0.00130242	40.0380723
61	0.0013338	0.00130115	40.6980249
62	0.0013349	0.00130715	41.3590649
63	0.0013359	0.001305	42.0210356
64	0.001337	0.00130761	42.6837993
65	0.001338	0.00130865	43.3472353
66	0.0013391	0.00130859	44.0112386
67	0.0013401	0.00130733	44.6757186
68	0.0013411	0.00132591	45.340597
69	0.0013421	0.00131062	46.0058073
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71	0.001344	0.00130676	47.3370044
72	0.0013449	0.00131022	48.0029027
73	0.0013458	0.00131282	48.6689534
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76	0.0013484	0.0013102	50.6677604
77	0.0013497	0.0013134	51.3341825
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79	0.0013523	0.00133278	52.6671729
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81	0.0013548	0.00131365	54.0002974
82	0.001356	0.00131837	54.6668934
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84	0.0013584	0.00131744	56.0001304
85	0.0013595	0.00131406	56.666765
86	0.0013606	0.0013236	57.3334072
87	0.0013617	0.00132227	58.0000553
88	0.0013627	0.00132345	58.6667079
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96	0.0013709	0.00132775	64.0000035
97	0.0013722	0.00132641	64.6666692
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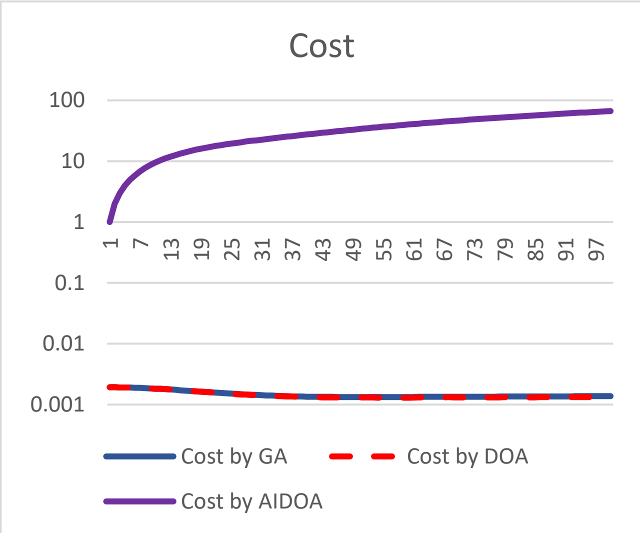

Fig. 4.2. A comparison of cost incurred by GA, DOA and AIDOA

The optimized code for the AIDOA has resulted in actual costs being shown as compared to the error of the calculation in the cost of GA and DOA, confirmed by meticulous refactoring of the code and multiple re-runs.

4.3 Comparison of Efficiency

A comparison of the Efficiency by DOA and AIDOA and the Annual Energy Production (AEP) by AIDOA

No of Turbines	Efficiency by DOA	Efficiency by AIDOA	AEP by AIDOA
1	1.0000	1	3125.84832
2	1.0000	1	6251.69664
3	1.0000	1	9377.54496
4	1.0000	1	12503.3933
5	1.0000	1	15629.2416
6	1.0000	1	18755.0899
7	1.0000	1	21880.9382

8	1.0000	1	25006.7866
9	1.0000	1	28132.6349
10	1.0000	1	31258.4832
11	1.0000	1	34384.3315
12	1.0000	1	37510.1798
13	1.0000	1	40636.0282
14	1.0000	1	43761.8765
15	1.0000	0.99469832	46639.1412
16	1.0000	0.99306308	49666.6328
17	1.0000	0.99130406	52677.3243
18	0.9997	0.98575994	55464.0487
19	0.9996	0.98394173	58437.3992
20	0.9992	0.98258626	61428.312
21	0.9994	0.96946537	63638.4359
22	0.9991	0.96587958	66422.2474
23	0.9989	0.96836765	69620.3192
24	0.9990	0.96492862	72389.2925
25	0.9881	0.95087184	74307.0288
26	0.9982	0.96114485	78114.2185
27	0.9981	0.94692001	79918.0646
28	0.9979	0.95139762	83269.8903
29	0.9975	0.94527498	85688.7999
30	0.9976	0.93708474	87875.5427
31	0.9973	0.93332454	90440.3596
32	0.9982	0.93097169	93122.441
33	0.9968	0.92048899	94951.1954
34	0.9964	0.91413083	97152.767
35	0.9957	0.90657808	99183.8949
36	0.9953	0.90603328	101956.414
37	0.9957	0.90965059	105206.902
38	0.9948	0.89348519	106130.168
39	0.9957	0.90843585	110745.674
40	0.9954	0.87957041	109976.147
41	0.9948	0.8862704	113584.22
42	0.9950	0.87131577	114391.239
43	0.9950	0.89713106	120584.711
44	0.9937	0.88705046	122002.549
45	0.9937	0.86227861	121290.847
46	0.9925	0.85544858	123004.115
47	0.9923	0.86183502	126616.38
48	0.9920	0.86803374	130240.406
49	0.9919	0.84183847	128941.509
50	0.9914	0.84917265	132719.245
51	0.9911	0.84190945	134215.744
52	0.9912	0.84608043	137525.392
53	0.9904	0.83627601	138545.814
54	0.9913	0.82857775	139860.451
55	0.9888	0.82288923	141472.48
56	0.9904	0.82437762	144305.246
57	0.9858	0.82758431	147453.472
58	0.9874	0.82749668	150024.488
59	0.9888	0.80401707	148280.89
60	0.9883	0.80248553	150506.883
61	0.9891	0.80671263	153821.341
62	0.9844	0.79794989	154644.761
63	0.9859	0.78415559	154422.539
64	0.9839	0.78130555	156303.529
65	0.9830	0.78654763	159810.858
66	0.9830	0.78734566	162434.126
67	0.9839	0.7810485	163576.423
68	0.9701	0.77592992	164929.868
69	0.9813	0.76378779	164736.449
70	0.9824	0.75622847	165469.885
71	0.9842	0.77260943	171469.252
72	0.9816	0.76238918	171584.132
73	0.9796	0.77890106	177735.039
74	0.9805	0.77374878	178977.978
75	0.9794	0.75267458	176455.993
76	0.9816	0.75165798	178567.231
77	0.9792	0.7558869	181934.659
78	0.9809	0.74593337	181870.617
79	0.9649	0.7342948	181328.24
80	0.9826	0.73299611	183298.773
81	0.9790	0.74631955	188963.418
82	0.9755	0.7269962	186343.347
83	0.9804	0.72199295	187317.757
84	0.9761	0.72445349	190220.665
85	0.9787	0.7262009	192949.479
86	0.9716	0.70305449	188997.185
87	0.9726	0.7199547	195790.821
88	0.9717	0.72299927	198878.773
89	0.9749	0.71336209	198457.69
90	0.9772	0.70573347	198541.422
91	0.9676	0.70794535	201376.609
92	0.9653	0.69965337	201204.95
93	0.9725	0.70114458	203825.46
94	0.9650	0.67924539	199582.498
95	0.9658	0.68932216	204698.07
96	0.9686	0.68259261	204833.374
97	0.9695	0.68184342	206739.895
98	0.9533	0.67627961	207166.852
99	0.9598	0.68655495	212460.598
100	0.9613	0.68218478	213240.614

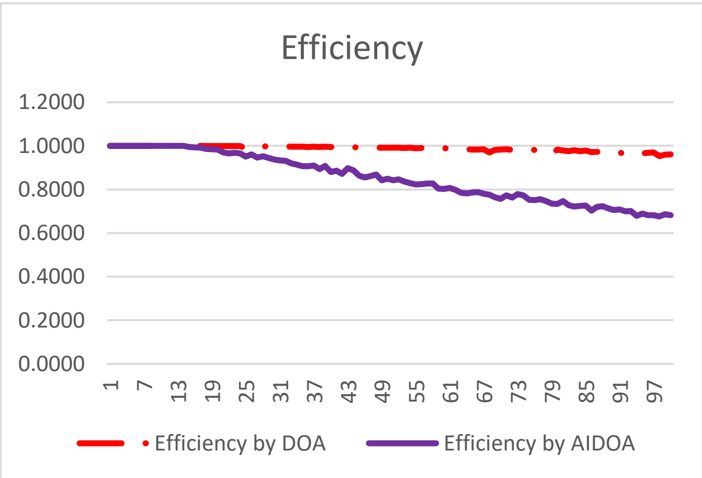

Fig. 4.3. A comparison of Efficiency DOA and AIDOA

The decay graph of the efficiency is accurately calculated, made possible by correcting the error in the code arriving at the justified decay graph.

4.4 Summary of Results

Statistic	TotalPower	TotalCost	Efficiency	AEP
Average	40616.973	34.624	0.8501	124531.63
Std Deviation	19770.434	18.380	0.1084	60616.14

This above table presents performance statistics for the Wind Turbine Micrositing simulation. The average values show a total power of 40,617 units, and a total cost of 34.62 which is dimensionless, efficiency of 85%, and Annual Energy Production (AEP) of 124,532 units. The standard deviations indicate significant variability in the data, with total power (at 19,770kWh), AEP (at 60,616 kWh) showing particularly high variation and efficiency remains relatively stable exhibiting only a 10.8% deviation.

4.5 Discussion

The results of AIDOA show variance as it is evident that a small number of generations of the population are simulated. It is anticipated that with a greater number of iterations, the results will smooth out.

The results of the power generation are favorable and clearly show that a greater amount of power is generated per unit turbine. The results of the cost in this study are realistic as they were incorrectly reported in literature, attributed to a Matlab error, while the refactored and rebuilt code of AIDOA gives a realistic output of the increasing cost of the turbines involved. Again the error in earlier literature as in the case of the efficiency is evident. Since, efficiency is a function of the total power divided by the total cost a more realistic graph of this parameter is attained in the refactored code.

5. Limitations

The limitations of the earlier code were clearly seen and a crisp and refactored code, on Matlab 2017b, running on a Core i7, 7th generation machine, improved the viewpoint on this important chapter of optimization.

Due to the processing overhead of the Adam algorithm a much lesser number of iterations were run for every turbine number. However, this is just the beginning and not the final word on this interesting NP hard problem.

With the advent of cluster computing and utilization of higher dimensions it is possible to apply AIDOA to a wide range of computational optimization problems of the modern era.

6. Conclusion

This paper introduced AIDOA, a novel optimization algorithm that combines the strengths of dynastic optimization and adaptive gradient-based methods. Applied to the challenging problem of wind farm layout optimization, AIDOA demonstrated a novel hybrid method for micrositing that offer promising results in solution quality and optimization efficiency as new machine learning adaptive rates are explored.

The key innovation of AIDOA - its adaptive follower generation mechanism - allows it to efficiently navigate complex, multimodal optimization landscapes without extensive parameter tuning. This makes it a promising tool not just for wind farm optimization, but potentially for a wide range of complex engineering and scientific optimization problems.

This algorithm may be applied to solar panel tracking algorithms but also to engineering problems where multiple dimensions exist and as it can mitigate the problem of further refinement of the solution space within the given computational cost and complexity.

7. Future work

Future work will focus on several directions, such as,

1) Multi-objective Optimization to extend AIDOA to directly handle multi-objective optimization exploration of the trade-offs between power output and cost. This could entail utilization of wind turbines with multiple heights as in [46].
2) Better Constraint Handling to develop specialized mechanisms for efficiently handling complex constraints in wind farm design, such as terrain features etc.
3) Exploring parallel implementations of AIDOA to leverage modern high-performance computing environments and potential application to new problems in optimization.
4) Developing a deeper theoretical understanding of AIDOA's convergence properties with particular focus on the optimal parameter settings and algorithm seeding in view of a stronger mathematical foundation of the algorithm.
5) Application to Other Domains including other complex optimization problems beyond wind farm layout including supply chain optimization etc.

6) Application to Solar panel tracking optimization problems is plausible and planned in future.

In conclusion, AIDOA represents a significant step forward in optimization algorithms, particularly for complex real-world problems like wind farm layout design. Its combination of global exploration and adaptive local search offers a powerful new tool for researchers and practitioners in renewable energy optimization and beyond.

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