A Comparative Analysis of Genetic Algorithm and Moth Flame Optimization Algorithm for Multi-Criteria Design Optimization of Wind Turbine Generator Bearing

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Abstract*: *As global climate change is affecting the meteorological conditions and instigating massive social suffering, the emanation of greenhouse gases is necessitated to be restricted through effective usage of renewable sources of energy as per the directions of the Paris treaty of 2015. Wind energy, a renowned renewable energy resource, is enabling countries to generate power in a relatively cost-effective way and causes a remarkably nominal carbon trail. A considerable extent of the functioning lifespan of wind turbines remains unexploited every year all over the globe because of mechanical malfunctions. The existing research strives to evaluate the relative competency of the Genetic Algorithm (GA) and the Moth Flame Optimization Algorithm (MFOA) for optimizing the wind turbine generator bearing design through enhancement of its static and dynamic load-bearing capacities. The design solutions attained by both of the algorithms validate a noteworthy growth of the optimization objectives when contrasted with the technical catalog standards. Moreover, the relative evaluation demonstrates the superior aptness of multi-criteria GA on multi-criteria MFOA for finding improved design resolutions.

***Keywords*: Wind Power, Wind Turbine Generator Bearing, Design Optimization, Moth Flame Optimization.**

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I. INTRODUCTION

Because of the escalating intercontinental anxiety aimed at the restrained hoard of non-renewable energy resources and their perilous impressions on the biome, renewable energy sources impart abounding replacements for the electricity generation industry [1]. Wind energy, especially, is an imperative and commercial approach for power generation [2]. Unswerving strives are on track to lessen the aggregate outlay of the wind power generation units as a consequence of curbing of the overheads associated with functioning and continuance commotions utilizing proper preventive and analytical policies [3]. As a result of the randomness of wind stream, unstable forces, and shifting power necessity, mechanisms of the Wind Turbine (WT) are susceptible to premature collapses inducing a sizable quantity of changeover expenses and disorders for the electricity distribution industry [4].

The generator is an essential component of WT and amenable to breakdown because of austere functioning circumstances and widespread disparity of forces [5]. The inoperative period prompted by generator interruption is reasonably substantial [6]. The flawed positioning of the gearbox and generator because of force function can intensify machining of the surface of Wind Turbine Generator Bearing (WTGB) [7]. Defects in the appropriate functioning of WTGB can be discovered by enhanced noise and quivering at the foundation [8]. Additionally, a data-steered procedure instituted on the sparse depiction and shift-invariant dictionary knowledge has been endorsed for locating inaccuracies in WTGB maneuvering [9]. Machine learning has been also utilized for anticipating the breakdown of WTGB [10]. Nevertheless, the utilization of Artificial Intelligence (AI)-driven multi-criteria design optimization of WTGB remained particularly constrained. AI techniques have been effectively commissioned in a range of industrial realms for optimizing single and multiple goals [11-13].

The present study purposes to improve the design of WTGB utilizing bio-motivated algorithms like Multi-Objective Genetic Algorithm (MOGA) and Multi-Objective Moth Flame Optimization Algorithm (MOMFOA) concurrently. The accomplished resolutions have been contrasted with trade catalog standards.

II. Problem Statement

Because of the aptness to undergo varied functioning states and intense rotating pace, the deep groove ball bearings are employed in a WT generator [14]. WTGB is necessitated to be fabricated to lower the mechanical resonance directing to untimely failure [15].

A. Objectives

The goals taken into account in the existing paper are expanding the static and dynamic capacities of the WTGB. The correlated functions have been concisely explained in the succeeding segments.

1. Static Capacity (C_{static})

The static load-withstanding capability is specified as the load operational on a motionless bearing that may impact the persisting disfigurement materializing at the spot of the topmost-loaded rotating constituent [16]. The static competence of the inner conduit can be formulated as per (1).

$$C_{static,internal} = \frac{23.8ZiD_b^{2}(a_i^{*}b_i^{*})^{3}\cos\alpha}{(4-\frac{1}{f_i}+\frac{2\gamma}{1-\gamma})^{2}} \tag{1}$$

In (1), z signifies the number of rotating constituents, i symbolizes the number of rows, D_b denotes the diameter of the rotating component, a_i* indicates the semi-major axis for the interior conduit, b_i* represents the semi-minor axis for the inner race, α indicates the contact angle, and f_i signifies the interior curvature parameter [16]. The static ability of the exterior race can be stated as per (2) [16].

$$C_{static,external} = \frac{23.8ZiD_b^{2}(a_o^{*}b_o^{*})^{3}\cos\alpha}{(4-\frac{1}{f_o}-\frac{2\gamma}{1+\gamma})^{2}} \tag{2}$$

In (2), a_o* characterizes the semi-major axis for the outside race, b_o* designates the semi-minor axis for the exterior conduit, and f_o symbolizes the peripheral curvature parameter [16]. γ can be calculated as per (3) [16].

$$\gamma = \frac{D_b\cos\alpha}{D_m} \tag{3}$$

In (3), D_m depicts the pitch diameter. The static load enduring capability can be computed as per (4) [16].

$$C_{static} = \min(C_{static,internal}, C_{static,external}) \tag{4}$$

2. Dynamic Capacity ($C_{dynamic}$)

Dynamic load sustaining competence is indicated as the invariable radial load that a range of noticeably alike bearings is able to endure for a review lifetime of one million rolls of the interior conduit [16]. It can be computed as per (5).

$$C_{Dynamic} = \begin{cases} f_c z^{\frac{2}{3}} D_b^{1.8}, & D_b \le 25.4 \\ 3.647 f_c z^{\frac{2}{3}} D_b^{1.4}, & D_b > 25.4 \end{cases} \tag{5}$$

In (5), f_c is a geometry-linked co-efficient reliant on f_i, f_o, and γ.

B. Constraints

The WTGB operated for 1.5 MW WT has been considered in the current study. Any standard engineering optimization problem is commonly related to one or several restraints. The constriction functions endorsed by Duggirala et al. [12] have been employed in the current work. They have been expressed in the following way.

$$\frac{\theta}{2\sin^{-1}(\frac{D_b}{D_m})} - z + 1 \ge 0 \tag{6}$$

In (6), θ denotes the assembly angle.

$$2D_b - \kappa_{D_1}(D_1 - D_2) \ge 0 \tag{7}$$

$$\kappa_{D_2}(D_1 - D_2) - 2D_b \ge 0 \tag{8}$$

In (7) and (8), κ_{D1} and κ_{D2} are geometry-linked factors varying between 0 and 1. D_1 and D_2 denote the external and internal diameter respectively.

$$\delta B - D_b \le 0 \tag{9}$$

In (9), δ is a non-negative and non-zero fractional parameter and B is the bearing width.

$$D_m - (0.5 - \varphi)(D_1 + D_2) \ge 0 \tag{10}$$

$$(0.5 + \varphi)(D_1 + D_2) - D_m \ge 0 \tag{11}$$

In (10) and (11), φ is a non-negative and non-dimensional parameter.

$$0.5(D_1 - D_m - D_b) - \varepsilon D_b \ge 0 \tag{12}$$

In (12), ε is a non-zero fraction. The variable value restraints have been presented in the following manner.

$$58 \le B \le 65 \tag{13}$$

$$280 \le D_1 \le 320 \tag{14}$$

$$130 \le D_2 \le 150 \tag{15}$$

$$20 \le D_b \le 35 \tag{16}$$

$$0.515 \le f_i \le 0.52 \tag{17}$$

$$0.515 \le f_o \le 0.52 \tag{18}$$

$$0.6 \le \kappa_{D_1} \le 0.7 \tag{19}$$

$$0.4 \le \kappa_{D_2} \le 0.5 \tag{20}$$

$$6 \le z \le 10 \tag{21}$$

$$0.3 \le \varepsilon \le 0.4 \tag{22}$$

$$0.6 \le \delta \le 0.85 \tag{23}$$

$$0.02 \le \varphi \le 0.1 \tag{24}$$

III. Optimization Algorithms

In the present study, the enhancement of the static and dynamic load enduring capacities for WTGB has been endeavored to apply MOGA and MOMFOA to assess their comparative efficacy. The optimization algorithms have been succinctly explicated in the subsequent segments.

A. Multi-Objective Genetic Algorithm (MOGA)

Genetic Algorithm is designated as an AI-emboldened searching method to suggest solutions for optimization tryouts by simulating the stratagem of biologic inclination respecting the plan of Turing to form a 'wisdom device' approximating the logic of evolution [17]. The MOGA to recognize non-subdued outcomes for multi-criteria design optimization of WTGB has been depicted in the following manner [11,13].

1. Organize different parameters allied to MOGA like populace magnitude, peak repetition count, percentages for crossover, and mutation techniques.
2. Form an introductory populace arbitrarily.
3. Examine the suitability of all chromosomes.
4. Employ the crossover system in the subsequent means.
   - 4.1 Pick out the chromosomes for the crossover scheme.
   - 4.2 Activate the crossover system.
   - 4.3 Authenticate the possibility of the descendants.
   - 4.4 If the posterities are operable, amalgamate them into the new generation.
5. Complete the mutation technique in the subsequent means.
   - 5.1 Elect the chromosomes for mutation activity.
   - 5.2 Instigate the mutation method.
   - 5.3 Verify the attainability of the recently produced chromosomes.
   - 5.4 If the generated chromosome is attainable, combine it into the latest generation.
6. Appraise the aptness of the novel chromosomes shaped by crossover and mutation measures.
7. Apply the preeminence valuation.
8. If the satisfactory count of chromosomes critical for Pareto optimal front composition has been realized, conclude the procedure, else restart.
9. Identify the extremely venerable outcome in proportion with the appraiser's prejudice.

The flowchart of MOGA is presented in Fig. 1 [11].

Fig. 1. MOGA Flowchart

B. Multi-Objective Moth Flame Optimization Algorithm (MOMFOA)

Mirjalili [18] recommended the moth flame optimization algorithm replicating the path tracing of the moths. It has been engaged in plentiful industrial fields for optimizing diverse objectives [19-21]. MOMFOA has been pithily articulated as follows.

1. Arrange the elementary factors for MOMFOA such as moth populace and flame sites.
2. Create the initial moths at random.
3. Examine the fittingness for moth distinctly.
4. Modify the flame worth, moth positions, and merger proportion.
5. Inspect the interim space within a moth and its compatible flame.
6. Adjust the population of moths.
7. If the ending standards have been achieved, conclude the procedure, else return to step 3.
8. Enlist the acclaimed states of the moths.

The architecture of MOMFOA has been shown graphically in Fig. 2 [22].

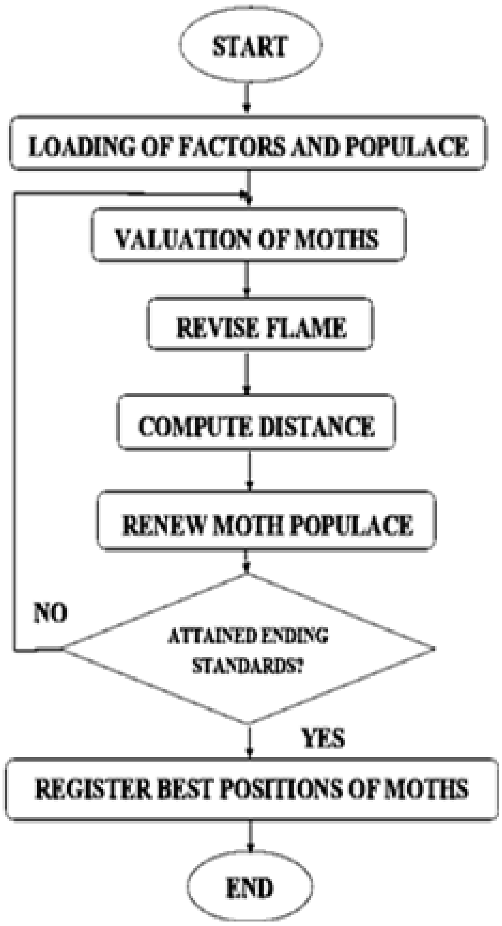

Fig. 2. MOMFOA Flowchart

IV. Results and Discussions

In the current optimization process, a population magnitude of 300 has been deemed for both algorithms. The optimization processes have been repeated for 300 epochs. The static and dynamic competencies of the WTGB have been measured in kN. The Pareto fronts achieved applying MOGA and MOMFOA have been displayed in Figs. 3 and 4 respectively.

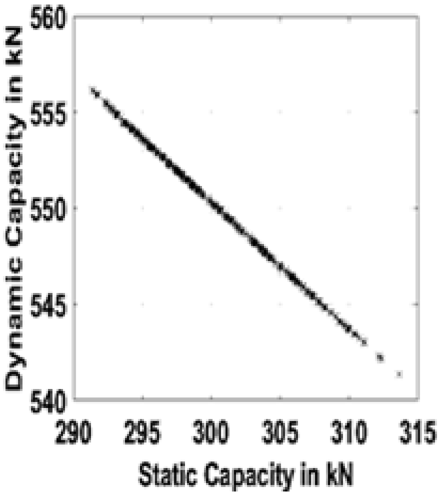

Fig. 3. Pareto Front Attained by MOGA

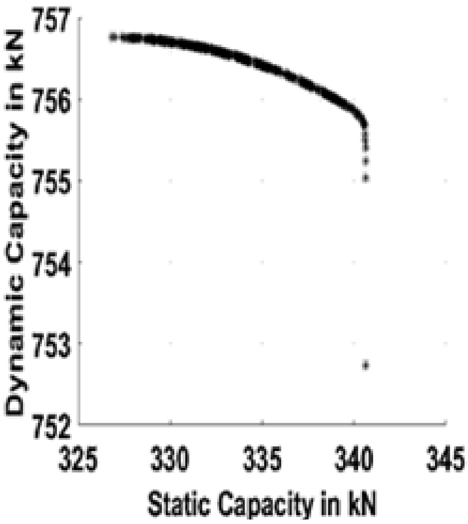

Fig. 4. Pareto Front Attained by MOMFOA

The optimal results attained by MOGA and MOMFOA have been shown in Table 1.

TABLE I. Comparison of Optimal Results

	Highest Static Capacity (in kN)	*Highest Dynamic Capacity (in kN)*
Catalogue Standard	280	360
MOGA Results	313.6514	556.1527
MOMFOA Results	340.6390	756.7605

The graphic representation of the optimization solutions attained using MOGA and MOMFOA validate the noteworthy enhancement of static and dynamic load enduring capacities of WTGB for both algorithms. Moreover, the comparative analysis of Pareto optimal fronts achieved by both the algorithms verify that MOMFOA offers more optimal design solutions than MOGA for every considered objective.

V. Conclusion

Generator Bearing is a vital apparatus of WT and liable for the untimely malfunction leading to a loss in operational life. In the present paper, AI-empowered procedures like MOGA and MOMFOA have been engaged concurrently to enhance the design of WTGB. Optimization solutions validate a significant increase in static and dynamic load-bearing capacities for both algorithms. The relative study confirms the superior suitability of MOMFOA over MOGA for optimizing the design of WTGB.

This research can originate pioneering potentials for more WT devices to lessen the losses in effective phase and commercial return owing to mechanical breakdowns by adroitly improving their preventive design scheme. The application arena can be broadened to more renewable energy generation fields with the utilization of more AI procedures.

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