A RELATIVE STUDY OF GENETIC ALGORITHM AND MOTH FLAME OPTIMIZATION ALGORITHM FOR MULTI-CRITERIA DESIGN ENHANCEMENT OF WIND TURBINE ACTUATOR BEARING

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Abstract

To curb the surge of worldwide climate change, renewable energy generation units like wind farms need to stay fiscally reasonable for empowering the green power conversion. A significant portion of the profitability of wind farms is lost each year across the globe to mechanical breakdown. This present paper aims to optimize the design of wind turbine actuator bearing using artificial intelligence techniques to enhance operational life. Two Bio-inspired algorithms like multi-objective genetic algorithm and multi-objective moth flame optimization algorithms have been employed simultaneously to maximize the static and dynamic capacities of the wind turbine actuator bearing. The analysis outcomes demonstrate the higher proficiency of the multi-objective moth flame optimization algorithm over the multi-objective genetic algorithm to optimize the considered objectives subjected to similar constraints and other optimization parameters. The solutions attained using both the optimization algorithms confirm a significant increase in static and dynamic capacities of the wind turbine actuator bearing when compared with the standard industrial catalogue values.

Keywords: Wind Power, Actuator Bearing, Multi-Objective Genetic Algorithm, Multi-Objective Moth Flame Optimization, Design Optimization

JEL Classification: -

1. Introduction

The unremitting emanation of greenhouse gases to the surroundings because of numerous societal doings is swelling the air temperature and anomalous climatological situations. As a result of the universal trepidation for the constrained supply of fossil fuels and their grave forfeits on flora and fauna, renewable sources of electricity impart proliferating locums.

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Surprisingly, the utilization of renewable energy expanded by 3% in 2020, while the necessity for non-renewable fuels crashed across the world. Wind energy, specifically, is an imperative and economical approach to renewable power generation. Universally, the charge of power generation from airstream has minimized precipitously over the past decades.

In India, the generation cost of wind power is already 35% lesser than that of the electricity generation establishments principally reliant on coal and this is tending to another reduction of 7% in 2022. Systematic ventures are underway to curtail the overall charge of the Wind Power Generation (WPG) by reducing the expenditures associated with operative and maintenance undertakings engaging safety and prognosticative actions.

Studies affirm that mechanical breakdown is accountable for 55.90% of the complete value of insurance entreaties and 32.50% of the full number of appeals related to WPG. The profit shortages underwent by the WPG segment because of the WT malfunction can vary from 200 M€ in Spain or 700 M€ in the whole region of Europe to 2200 M€ in the remaining regions of the Earth.

2. Literature Review

Gallego-Calderon et al. (2015) analyzed the consequence on reliability for Cylindrical Roller Bearing and Tapered Roller Bearing arrangements of planetary bearings of WPG system gearbox. Ni et al. (2017) considered the issues allied to the rolling element bearing of WPG transmission assembly by applying the field data of the Lu Nan wind farm of PR China. Micha et al. (2017) recommended the appliance of stable magnetic bearing in vertical axis small WT employing finite element analysis and multi-physics software for enhancing the turbine speed and revolving phase.

Stammler et al. (2018) investigated the impact of oscillation on the damaging lifetime of WT pitch rolling bearing. Schwack et al. (2020) checked the influence of grease lubricants on abrasion of WT pitch bearing. Fuentes et al. (2020) recommended a technique to recognize the sub-surface dent of WT bearings with sound release and probabilistic representation. Nicholas et al. (2020) proposed an inventive ultrasonic reflectometry approach to analyze the loading and lubrication condition of WT high-speed shaft bearing utilizing piezoelectric transducers.

The studies conducted on WT bearings are mostly mono-objective and the optimization of WT actuator bearing is yet to be explored. The present study aims to optimize the design of actuator bearing of Wind Turbine (WT). Due to the involvement of multiple objectives, Artificial Intelligence (AI) techniques have been utilized in the current design optimization situation. AI-enabled approaches have been exercised across numerous engineering fields for their robustness and computational proficiency.

In the current work, the Multi-Objective Moth Flame Optimization Algorithm (MOMFOA) has been proposed for optimizing the design of the WT actuator bearing. The optimization results have been contrasted with the same realized using the Multi-Objective Genetic Algorithm (MOGA) and engineering catalogue standards to estimate their comparative effectiveness.

3. Objective Function

The goal parameters taken into account in the present study are maximization of the static and dynamic capacities of the WT actuator bearing. The objective functions have been concisely reviewed in subsequent segments.

3.1 Static Capacity (C_{static})

The static capacity is termed as the load functioning on an immobile bearing that can impact the long-term alterations ensuing at the spot of the topmost-burdened rotating constituent. The static capacity for the internal race ($C_{static,\ internal}$) can be calculated as per Eq. (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 Eq. (1), z signifies the quantity of revolving elements. i characterize the count of rows of balls. D_b represents the diameter of rolling elements. a_i* and b_i* denote the dimensionless semi-major and semi-minor axes for the internal ring respectively. α stands for the contact angle. f_i is the internal curvature parameter. The static capacity of the external race ($C_{static,\ external}$) is formulated using Eq. (2).

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

In Eq. (2), a_o* and b_o* represent the dimensionless semi-major and semi-minor axes for the external race respectively. f_o stands for the external curvature parameter. γ is evaluated using (3).

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

In Eq. (3), D_m represents the pitch diameter of the bearing. The static capacity of the entire bearing can be formulated as per Eq. (4).

$$C_{static} = min\ (C_{static,inner}, C_{static,outer}) \tag{4}$$

3.2 Dynamic Capacity ($C_{dynamic}$)

The Dynamic capacity of rolling-element bearing can be defined as the firm radial load, which a pool of speciously alike bearings can stand for a valuation lifecycle of one million spins of the interior raceway. It can be defined using Eq. (5).

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

In Eq. (5), fc is a geometry-related parameter.

4. Constraints

The constraints specified by Duggirala et al. (2018) have been implemented in the present work. The rolling element number and rolling element diameter are related as per Eq. (6).

$$S_1(X) = \frac{\phi_0}{2\,sin^{-1}\left(\frac{D_b}{D_m}\right)} - z + 1 \geq 0 \tag{6}$$

In Eq. (6), ϕ_0 symbolizes the bearing assembly angle. The rolling element diameter is maintained within a limit as per Eqs. (7) and (8).

$$S_2(X) = 2D_b - K_{D_{min}}(D - d) \geq 0 \tag{7}$$

$$S_3(X) = K_{D_{max}}(D - d) - 2D_b \geq 0 \tag{8}$$

In Eqs. (7) and (8), D and d represent the external and internal diameters of the bearing respectively. K_{Dmin} and K_{Dmax} are fractional parameters between 0 and 1. They are related to the bearing geometry. Bearing thickness is associated with the rolling element diameter as per Eq. (9).

$$S_4(X) = \zeta B_w - D_b \leq 0 \tag{9}$$

In Eq. (9), ζ is a fractional factor between 0 and 1. The pitch diameter can be evaluated as per Eqs. (10) and (11).

$$S_5(X) = D_m - (0.5 - e)(D + d) \geq 0 \tag{10}$$

$$S_6(X) = (0.5 + e)(D + d) - D_m \geq 0 \tag{11}$$

In Eqs. (10) and (11), e is a parameter ranging between 0 and 1. The breadth at the exterior raceway is related to pitch diameter and rolling element as per Eq. (12).

$$S_7(X) = 0.5(D - D_m - D_b) - \varepsilon D_b \geq 0 \tag{12}$$

In Eq. (12), ε is a fractional parameter between 0 and 1.

5. Optimization Algorithm

Each usual design optimization procedure comprises several aims allied to a constituent domain and single or multiple constrictions. Every multi-criteria optimization may be quantified using Eq. (13).

$$Minimize/Maximize\, f_t(x), \quad t = 1,2,\ldots T;$$

$$subject\ to,\ S_i(x) \geq 0, \quad i = 1, 2, \ldots I;$$

$$h_j(x) = 0, \quad j = 1, 2, \ldots J;$$

$$x_k^{(L)} \leq x_k \leq x_k^{(U)}\ k = 1, 2, \ldots K.$$

(13)

In Eq. (13), x signifies the evaluation vector, $f_t(x)$ stands for the t^{th} goal, $S_i(x)$ symbolizes the i^{th} inequality constriction, and $h_j(x)$ represents the j^{th} equality restriction.

The collection of non-subjugated resolutions shapes the Pareto optimum frontage. MOGA and MOMFOA have been engaged in the current study to maximize the static and dynamic capacities of WT actuator bearing.

The algorithms have been briefly described in the following sub-sections.

5.1 Multi-Objective Genetic Algorithm (MOGA)

Genetic Algorithm (GA) is a bio-stimulated exploration method to recommend resolutions for optimization efforts to emulate the progression of biological choice as projected by Turing. MOGA has been applied to optimize numerous aims correlated to various technical domains.

The MOGA employed in the existing study has been offered as follows.

1. Appoint the parameters of MOGA.
2. Organize the initial chromosomes arbitrarily.
3. Analyze the appropriateness of all chromosomes.
4. Execute the arithmetic crossover procedure.
5. Accomplish the mutation technique.
6. Examine the aptness of the existing entities shaped utilizing crossover and mutation measures.
7. Complete the dominance estimation.
8. If the satisfactory count of solutions vital for Pareto frontage composition is realized, then terminate, else recommence.
9. Pick out the utmost brilliant and agreed resolution consistent with the assessment maker's penchant.

5.2 Multi-Objective Moth Flame Optimization Algorithm (MOMFOA)

Being inspired by the direction-finding of the moth, Mirjalili (2015) proposed the Moth Flame Optimization Algorithm (MFOA).

MFOA has been utilized in several engineering applications. MOMFOA can be briefly stated as follows.

1. Initialize the factors for MOMFOA.

2. Create the preliminary moths arbitrarily.
3. Compute the aptness for each moth and label the finest locations concerning the flames.
4. Revise the flame count, moth position, and convergence rate.
5. Compute the gap between a moth and the corresponding flame.
6. Modify the population of moths.
7. If the termination criteria are accomplished, then finish, else return to step 3.
8. Register the preeminent locations of the moths.

6. Appliance

In the present research study, WT actuator bearing has been taken into account.

The related parameters have been sustained within rigid boundaries following the engineering catalogue obtainable for WT of power rating from 1.5 MW to 3.0 MW.

B_w	~ {16,22}
d	~ {25,80}
D	~ {62,125}
D_b	~ {8,15}
D_m	~ {0.5(D-d), 0.6(D-d)}
e	~ {0.02,0.10}
f_i	~ {0.515,0.52}
f_o	~ {0.515,0.52}
K_{Dmax}	~ {0.6,0.7}
K_{Dmin}	~ {0.4,0.5}
ε	~ {0.3,0.4}
ζ	~ {0.6,0.85}

Table 1 Limits of Parameters

7. Results and Discussion

For both the optimization algorithms, the considered population dimension has been 200. MOGA and MOMFOA have been iterated 200 times. The static and dynamic capacities of the deep-groove WT actuator bearing have been measured in kN. The Pareto fronts achieved for both the optimization algorithms have been displayed in Figs.1 and 2.

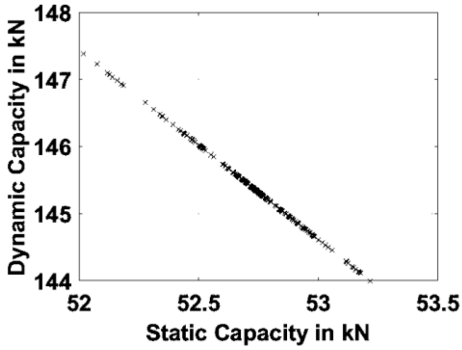

Figure 1. Pareto Front Obtained using MOGA

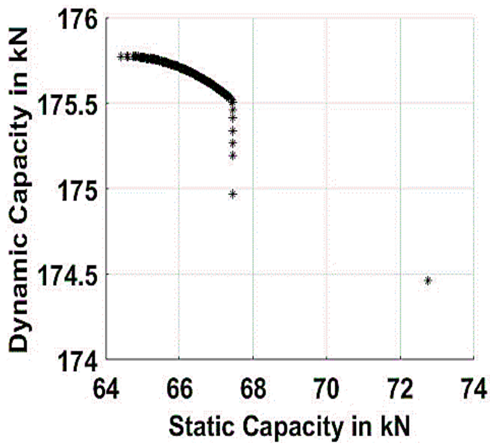

Figure 2. Pareto Front Obtained using MOMFOA

The graphic illustrations of the optimization run applying the projected MOMFOA demonstrate more optimized results while contrasted with the solutions achieved using the MOGA method for analogous aims and constrictions.

The optimization outcomes attained using both of the AI-enabled algorithms have been compared with the standard engineering catalogue values and a significant increase in the objectives has been proved.

8. Conclusion

The results of MOMFOA ascertain a noteworthy growth in static and dynamic capacities of WT actuator bearing when evaluated against technical catalogue standards and the outcomes achieved using MOGA.

This study would initiate new openings for other WT apparatuses to decline the deficits in the operative period and fiscal return because of mechanical failures by competently refining the design procedure.

The appliance arena can be pushed to further renewable power generation mechanical mechanisms. More AI applications may be applied in the upcoming period for design optimization.

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