

Multi-objective drone propeller optimization using genetic algorithms (GA) for enhanced thrust and silent operation

Sayujya Karnik^{1*}, Nitin Kataria¹, Disha Dixit¹, Palak Agrawal¹, Yogesh Pandya¹, and Sudhir Chaurey¹

¹Prestige Institute of Engineering Management and Research, Indore, M.P., 452010, India

Abstract. Optimizing drone propeller performance is essential for the enhancing thrust generation and reducing the acoustic noise under real world operation. In this study, we use multiple optimization techniques like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA) to determine the optimal geometric parameters for the drone propellers. The optimization process is designed based on the drone's weight and the RPM generated by the motor, to improve its aerodynamic performance. The approach focuses on the optimization of key geometric features such as propeller radius, chord length, pitch, twist, and sweep and other geometric characteristics like maximum thickness of the propeller, cross-section, centre of gravity in Y and Z axis, while keeping the propeller material as constant. By comparing the optimal parameters from different optimization methods, we show that while each technique effectively identifies high-performance configurations, the complementary use of these methods enhances the validation of our optimized parameters. Although the current study does not include material optimization, this aspect is a promising direction for future research.

1 Introduction:

Several studies have explored where noise in propeller design comes from and suggested ways to reduce it. Sutcliffe et al. [1] took a close look at this issue and found that blade-vortex interaction, blade-tip vortices, and shockwaves from high tip speeds are the main reasons behind propeller noise. They pointed out that slowing down the blade tips and improving the overall shape of the blades, like adjusting the angles and profiles, can help bring noise levels down quite a bit. What's more, they suggested that using variable pitch blades could reduce noise during different stages of flight, making it a more adaptable solution.

Sullivan and Avery [2] also studied how changes to blade tips could make a difference in controlling noise. They tested winglets and tapered blades to see how these modifications worked. Their results showed that winglets were especially good at weakening tip vortices,

* Corresponding author: karnik.sayujya@gmail.com

which led to less noise being produced. This shows how important it is to focus on blade design and make small adjustments to how drones operate to keep them quieter.

This research has some pretty big takeaways for making drones quieter in the future. By tweaking the shape of the blades and improving how drones move through the air, manufacturers can make drones perform better while also dealing with the problem of noise pollution. This is becoming more important for things like urban air mobility, wildlife monitoring, and surveillance work. As researchers keep digging into this topic, we're likely to see even better designs that balance performance with environmental concerns.

The tapered blade tips also reduce turbulent flow near the blade tips, which helps in quieter flight. The contradictory nature of thrust and noise reduction requires a multi-objective optimization approach. Other optimization methods like genetic algorithms (GA) have been used for optimizing the thrust as well as noise in propeller designs together. Zhang et al. [3] employed a genetic algorithm to optimize two-objective drone propeller design, thrust maximization, and noise minimization. The study showed GA's capability to find Pareto-optimal solutions effectively, providing a set of the best compromise alternatives between thrust and noise. Their research highlighted the necessity of optimizing GA parameters such as crossover rate, mutation rate, and population size to achieve accurate results. In different research, Mocellin et al. [4] used multi-objective evolutionary algorithms to design drone propellers. They found that evolutionary algorithms were able to provide a wider range of optimal solutions compared to random optimization methods, and thus providing higher flexibility in design alternatives. Their contribution also focuses on including physical constraints (e.g., material properties, structural integrity) in the process of optimization to ensure that solutions obtained were reliable for everyday applications. Kumar and Patel [5] explored the implementation of Pareto front analysis as a means to perform multi objective optimization for drone propellers. By showing the trade-offs between thrust and noise for different propeller designs [6,7]. They were able to find the optimal design points where the thrust increase was improved without causing excessive rises in noise. UAV propeller design comes about due to a subtle interplay between aerodynamic and acoustic performance. Traditional methods of propeller design tend to address either thrust production or power efficiency, typically at the expense of noise reduction [8,9]. However, in most cases particularly where stealth or minimal disturbance is required the acoustic signature of UAVs is a prime design requirement. This absence of concern in classical design methods emphasizes the need to take an integrated approach that balances both aerodynamic and acoustic objectives. This work addresses the issue of optimally balancing these conflicting objectives—maximum thrust generation and minimum noise, while designing UAV propellers [10,11]. We address this issue by introducing a multi-objective optimization process employing Genetic Algorithms (GA), an effective optimization technique. GA-based approach will offer the potential for searching the design space and finding optimal propeller configurations meeting the performance and the acoustic constraints. Through the inclusion of both these specifications within the design process, the objective is to enhance UAV operations in noise applications, introducing solutions with minimized noise operation that is flown more efficiently.

2 Methodology

The design of propellers for drones usually involves primarily thrust maximization and acoustic noise reduction. Optimized parameters are achieved using a multi-objective optimization approach to find the best trade-offs between the objectives.

A high propeller thrust is important for payload carrying capacity, endurance, and drone performance. The Factors Affecting the Thrust is the geometry of the Blade this includes the following parameters Blade length, pitch angle, and twist determine how the volume of air that the propeller moves [12]. The higher rotational speeds usually provide greater thrust. The shape and the aerodynamics of the blades also significantly contribute to thrust production [13].

Reduce the noise output of the propeller, critical in applications where there is a need for quiet operation, like surveillance, wildlife monitoring, and operations in urban areas [14].

The parameters that affect noise are blade geometry, shape and size of the blades, especially the design of the tip, heavily affect noise levels and increased rotational speeds tend to be associated with more noise. Tip speed blade tip speeds tend to produce shock waves, contributing to increased noise.

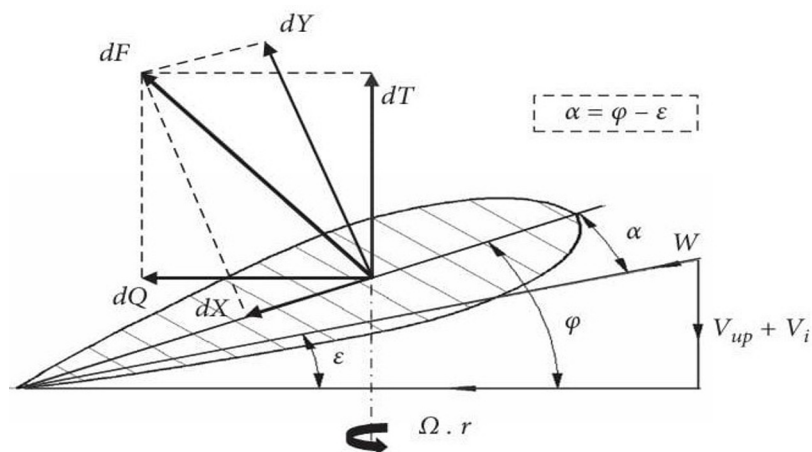


Fig. 1. Geometry of a 2D airfoil and components

As greater thrust can cause more noise, these two goals tend to compete with each other. A multi-objective optimization method assists in finding the optimal compromise between thrust and noise. The outcome is a collection of optimal solutions, referred to as the Pareto front, which gives the trade-offs between thrust maximization and noise minimization. The methodology employed to optimize drone propeller design by solving two main goals of thrust maximization and noise minimization [15]. This diagram shown in Fig. 1 illustrates Blade Element Theory (BET), which analyses the performance of rotating blades (e.g., propellers or wind turbines). It shows a blade element, a small 2D airfoil section at a specific radius. The key components are Velocities(V), Freestream velocity (Ωr), Rotational velocity (V_i), Induced velocity (W), Resultant velocity(dF), Forces: dF: Total force, dT: Thrust (along the axis), dQ: Torque (perpendicular to the axis), Angles (α), Angle of attack (ϕ), Flow angle(ϵ) and Blade pitch angle The design parameters are number of blades, length of chord, air foil shape, blade pitch, twist and length. The constraints include maximum length of blade, minimum thickness, structural strength, and properties of materials. Performance parameters are thrust coefficient (c_t), power coefficient (c_p), and noise level (db).The thrust coefficient (C_t) is taken as the measure of thrust. It is defined as the thrust produced by the propeller and the dynamic pressure and the reference area (normally the propeller blade swept area). The thrust coefficient is obtained from eq. (1):

$$C_t = \frac{T}{\frac{1}{2} \rho n^2 A} \quad (1)$$

where, T is the thrust, ρ is the air density, n is the rotational speed (in revolutions per second), and A is the area swept by the propeller blades. The noise level is usually in decibels (dB), which is a logarithmic scale of the acoustic power. The sound pressure level (SPL) is obtained using the formula given in eq. (2):

$$SPL = 10 \log_{10} \left(\frac{P_{acoustic}}{P_{ref}} \right) \quad (2)$$

Where, $P_{acoustic}$ is the acoustic power produced by the propeller, and P_{ref} is the reference acoustic power, which is usually 20×10^{-6} Pa in air. The efficiency of the propeller is measured by comparing the thrust produced with the power taken by the motor. Efficiency is expressed as the ratio of mechanical power output to the electrical power input. Greater efficiencies mean better power utilization of the motor for thrust generation.

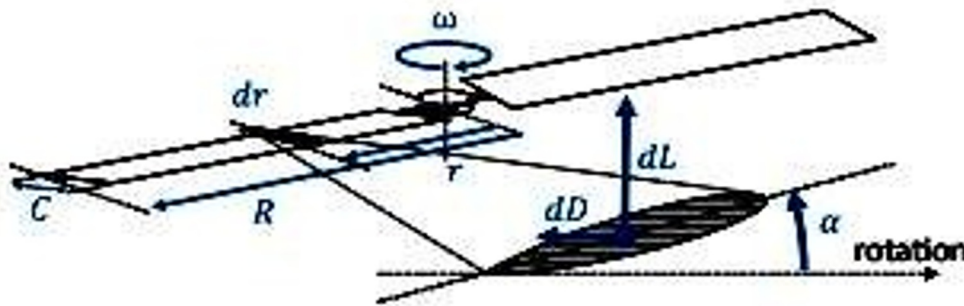


Fig. 2. Forces and moments acting on the flapping wing.

The moments and forces acting on a flapping wing, especially for the case of ornithopter or flapping-wing micro air vehicle (MAV) are depicted in Fig. 2. The main components in the figure includes, the wing with its root (r), chord (C), and rotation axis, flapping motion, symbolized by the omega (ω), denoting the rotational movement around the wing root, the aerodynamic forces are Lift (dL) and Drag (dD) produced by the wing, perpendicular and parallel to the flow of air, respectively, Thrust (T) that drives the aircraft forward and Angle of attack (α) is the angle between the wing chord and airflow direction. The rotation of the wing about its axis, is employed to regulate lift and thrust. The parametrization of the drone propeller design involves a number of important variables that affect the level of thrust as well as the noise level. The optimization variables are the ones that change as the Genetic Algorithm is employed for optimization. Some of the important design variables considered are the number of blades taken from 2 to 6. The physical constraints restrict the length of blades to 0.1 m to 0.3 m. The pitch angle is changed between 5° and 25° . Twist angles are limited between 0° and 15° . Chord lengths are changed from 0.02 m to 0.05 m. Various airfoil shapes are simulated, such as NACA 0012 (a symmetric airfoil) and NACA 4412 (a cambered airfoil). The propeller rotational speed is changed, as higher speeds can produce greater thrust but generally result in increased noise. A range of 3,000 to 10,000 RPM is used.

The maximum blade length of 0.3 m is taken into account because of physical and structural constraints. Minimum allowable thickness of chord: 0.005 m for structural integrity. The thickness of the airfoil should not be more than 10% of the chord to prevent excessive drag and noise. 2.3. Each propeller design is analyzed with both aerodynamic and acoustic simulations, and the important performance parameters are calculated afterward.

3 Results and Discussion

The propeller optimization of drones is a multi-objective problem, which is non-linear in nature and has conflicting objectives. GAs are appropriate for multi-objective problems since they can effectively search large solution spaces and obtain a set of optimal solutions that trade-off the conflicting objectives.

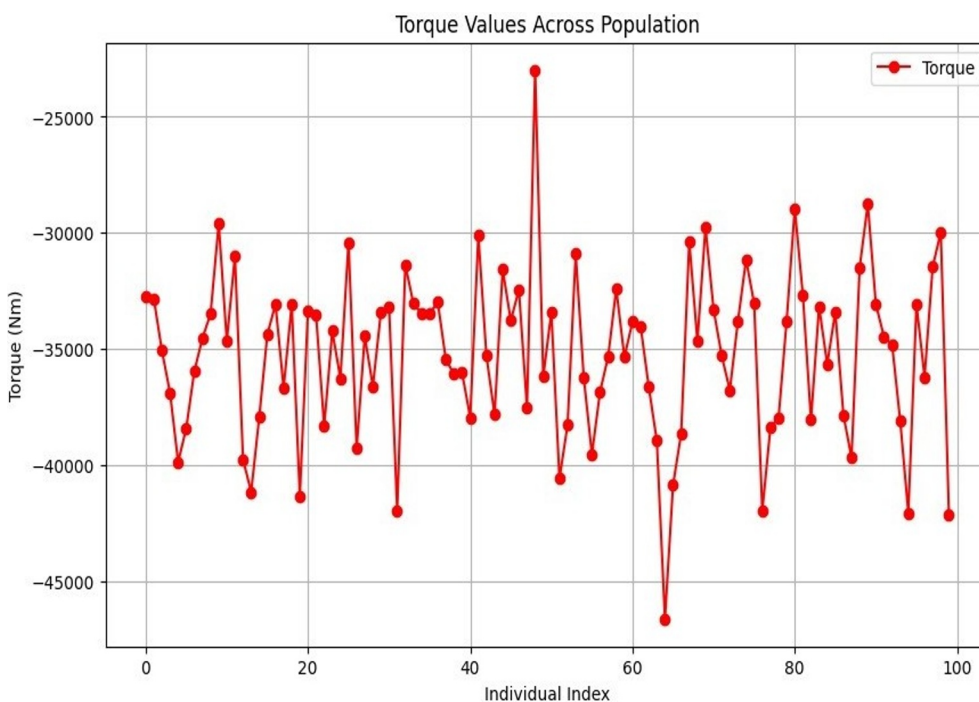


Fig. 3. Torque values across population

The graph in Fig. 3, illustrates the torque produced by each individual (potential propeller design) within the population during Genetic Algorithm (GA) optimization, x-axis representing the index of each individual within the population, y-axis representing the torque calculated value for that individual (in Nm - Newton meters). Interpretation aids in visualization of how torque values are distributed throughout the population. Lower torque values are generally desirable for efficiency, so you'd look for individuals with points lower. The procedure calls for the use of a multi-objective optimization approach, here a Genetic Algorithm (GA) used for browsing the trade-off across thrust and noise. Optimization is steered by a list of propeller design parameters, and the performance assessment is conducted using simulation-based techniques and key performance parameters. Tuning the genetic algorithm parameters (population size, crossover rate, and mutation rate) is a must for efficient optimization and convergence toward optimal points. The graph illustrated in Fig. 4 depicts the estimated noise level generated by each individual within the population, also during the GA optimization, x-axis that denotes the index of each individual within the

population, y-axis that denotes the noise level in decibels (dB). Interpretation: It facilitates visualization of the population's distribution of noise levels. Lower noise levels are typically desired, so you'd want to identify individuals with lower points on the graph.

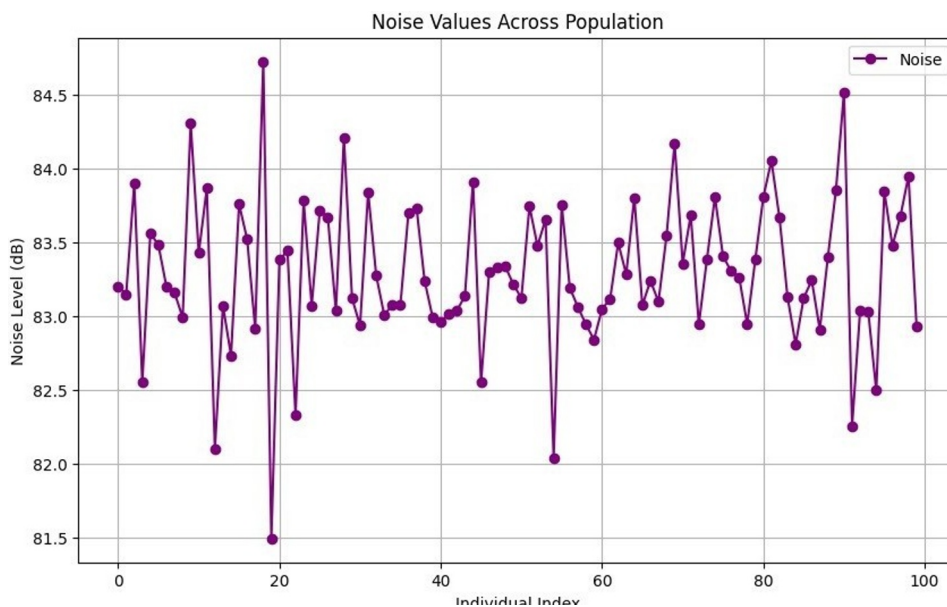


Fig. 4. Noise values across population

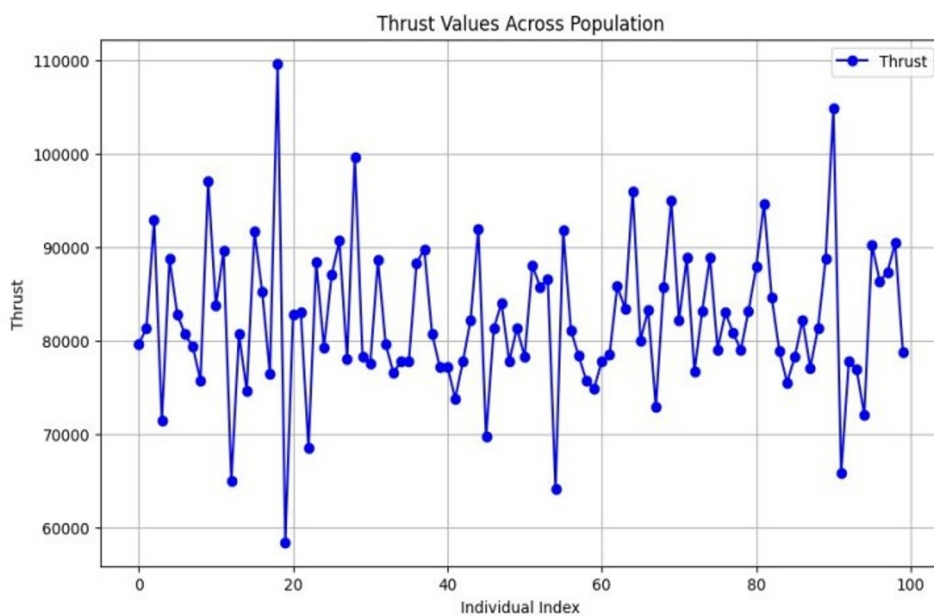


Fig. 5. Thrust values across population

The graph illustrated in Fig. 5 plots the thrust produced by each individual (candidate propeller design) in the population throughout the Genetic Algorithm (GA) optimization, x-axis representing the index of each individual in the population, y-axis representing the calculated thrust value for that individual. Interpretation: It serves to illustrate the distribution of the values of thrust within the population and select individuals with larger thrust. The greater the point on the graph, the greater the amount of thrust that specific propeller design is estimated to create.

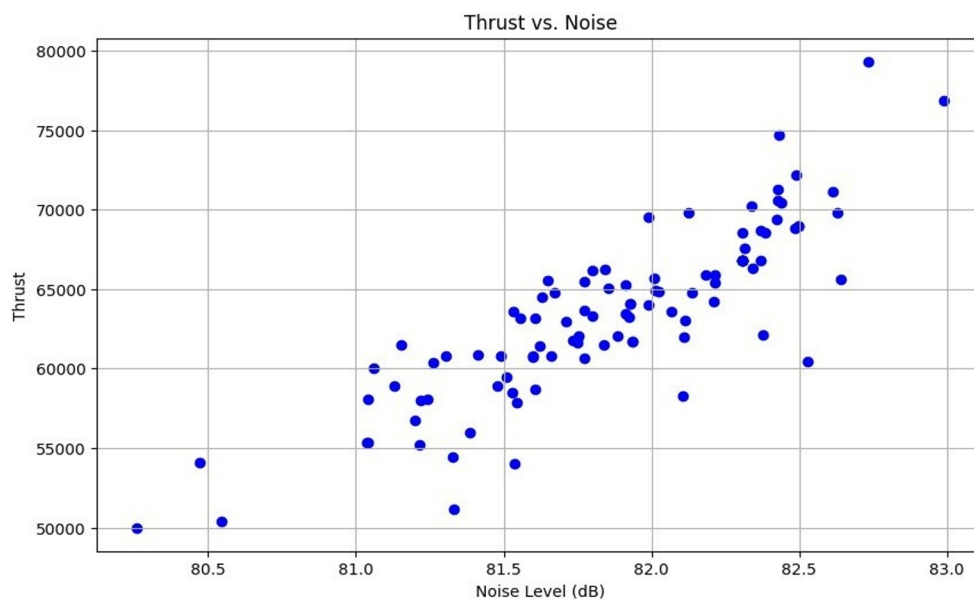


Fig. 6. Thrust vs Noise graph

The plot in Fig. 6 displays the relationship between the thrust that is produced by a propeller design and the noise produced. This graph contains one point per propeller design that was tested during optimization. X-axis: The noise level of the propeller, in decibels (dB). Larger values mean more noisy propellers. Y-axis: The thrust produced by the propeller. Higher values on this scale mean more energetic propellers. Use: The graph assists you in seeing the compromise between thrust and noise. You would ideally prefer a propeller with high thrust and low noise, which would be shown by points in the top-left part of the graph. Designs in the bottom-right part have low thrust and high noise, which are undesirable. The general trend of the points can give you an idea of the overall relationship between these two variables for your particular propeller designs. The approach involves a Genetic Algorithm for multi-objective optimization of drone propeller design, balancing thrust maximization with noise reduction. The most important design parameters are blade number, blade length, pitch angle, twist, chord length, and airfoil shape, all of which are modified in the optimization process. Performance assessment is done through aerodynamic and acoustic simulation and experimental validation for the verification of the optimized designs. The graph depicted in Fig. 7, plots the convergence of four optimization algorithms (Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, Differential Evolution) with iterations, x-axis representing the algorithm's iteration number, y-axis representing the best individual's fitness value (which is a sum of

thrust, torque, and noise) at that iteration. Interpretation: The plot indicates how rapidly each algorithm optimizes the propeller design in terms of the fitness function over time. The algorithm with the steepest curve and greatest final fitness is usually the most effective on the chart. In Fig. 8, there is a bar for each algorithm. The height of a bar is indicative of the time for the algorithm, in seconds. This graph is helpful for seeing at a glance the relative performance of algorithms. Higher bars for longer time, shorter bars for faster algorithms. The GA Parameters such as population size is 100 individuals per generation. Crossover rate is used at 0.85 to facilitate search of new combinations of designs. The mutation rate is used at 0.05 to guarantee diversity and avoid premature convergence. Number of generations: 200 generations to guarantee complete exploration of the design space.

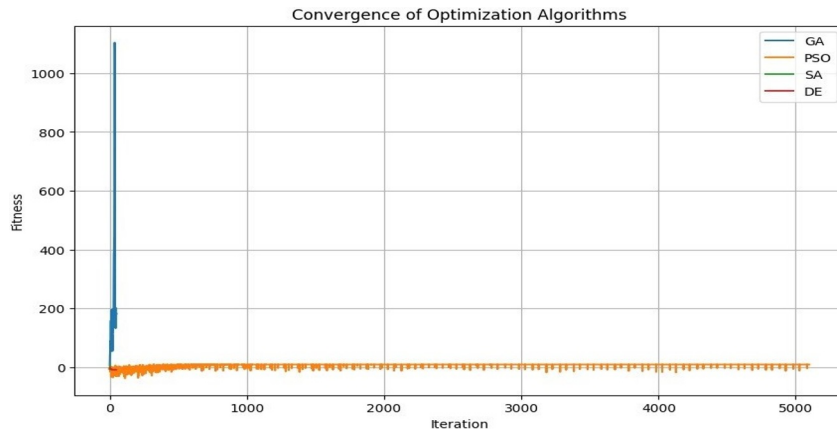


Fig. 7. Convergence of optimization algorithm

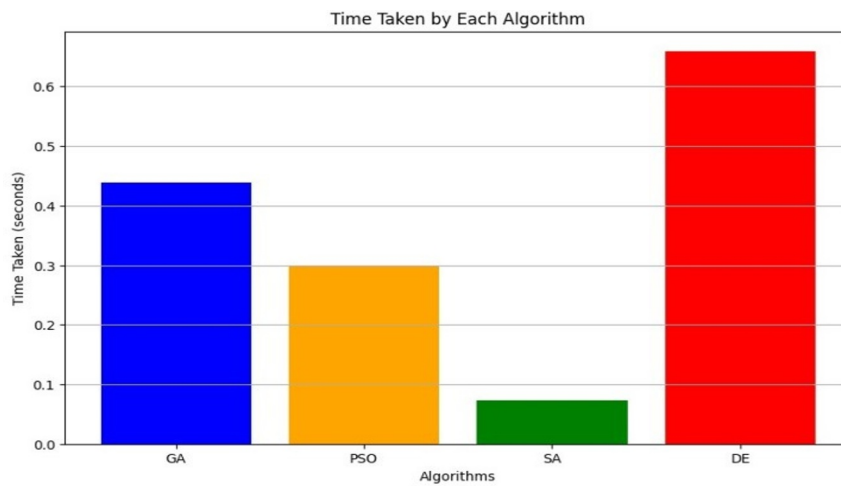


Fig. 8. Time taken by each algorithm

The outcome of multi-objective optimization of drone propellers with the aim of minimizing noise while maximizing thrust has been summarized. The optimization, carried out using a Genetic Algorithm (GA), resulted in a collection of Pareto-optimal solutions that denote the optimum trade-offs between both competing objectives. The outcome is studied based on convergence analysis and Pareto front analysis, which facilitate insight

into the efficacy of the optimization procedure and performance of the developed designs. Convergence analysis analyzes how well the Genetic Algorithm (GA) converges to an optimal solution across several generations. The objective is to have the algorithm consistently making progress towards the Pareto- optimal front and for the population not to converge prematurely to inferior solutions. The optimization process revealed consistent improvement in thrust and noise reduction with generations, as evidenced by the steady rise in the thrust coefficient and the corresponding fall in SPL. Early generations (1-50) were highly diverse in design parameters, enabling the GA to probe various regions of the design space. By generation 75 , the algorithm was already starting to show signs of convergence, with the population clumping around a smaller number of high-performing designs. But there was evident variability in the trade-off between noise and thrust, which indicated that the GA was not overfitting to a single design but was instead trying to balance the two goals. In later generations (150-200), the best-performing designs were found, with thrust coefficients attaining optimal values with respect to noise levels settling at the lowest possible levels.

The plot of convergence depicted a persistent trend of declining in the extent of thrust and SPL values, confirming that optimization was resulting in higher thrust and quieter designs through generations. It also revealed plateaus in subsequent generations, marking the advancement of the algorithm to the Pareto front, whereby further improvement on one objective would lead to the deterioration of the other. The Pareto front analysis is crucial for the visualization of the trade-offs between the two objectives: thrust and noise. The Pareto front is a collection of non-dominated solutions, in which no other solution can make one objective better at the expense of the other. This collection offers important insights into the range of feasible solutions that balance the conflicting objectives in an optimal manner. Once the Genetic Algorithm (GA) is started, the last population of individuals is examined to obtain the Pareto-optimal solutions. The solution is defined by two most important parameters Thrust and Sound Pressure Level (SPL) a metric of the noise produced by the propeller. Pareto-optimal solutions are those solutions in which no other design can improve thrust without worsening noise or minimize noise without reducing thrust. The correlation between thrust and noise levels is an essential consideration in propeller design for drones. Analysis of data indicates a direct relationship, with higher thrust outputs generally matched with more elevated noise levels. The noise levels fall between about 80.5 dB and 83 dB, with thrust values are from 50,000 to 80,000 units. In spite of some variation in the data, the trend is consistent, pointing out that improvements in thrust tend to be at the expense of high noise levels. This correlation points to the trade-off in propeller design, where optimizing for maximum thrust in operation can result in higher noise emissions. These observations are especially significant in applications that require low-noise operation, such as urban use or operation in noise-sensitive environments. Hence, the optimization of the propeller geometry for drones needs to follow a holistic approach, in addition to aerodynamic capability, noise attenuation measures. These could include, the investigation into novel materials, novel blade shape geometries, and aerodynamics improvements to procure a harmonized design that creates minimal noise with no loss in thrust efficiency. These findings pave the way to further research to develop sustainable, efficient drone technology.

The Genetic Algorithm (GA) efficiently searched the design space and converged toward a Pareto-optimal solution set that characterizes the optimum trade-offs between thrust and noise. Convergence analysis proved the stability and consistency of the optimization process, preventing the algorithm from converging too early to high-quality solutions. Pareto front analysis gave useful insights into the set of viable solutions, making it possible to choose designs for various requirements of operations. These findings

highlight the capability of multi-objective optimization in improving the design of drones' propellers, making them quieter and more efficient UAVs appropriate for a range of uses. Table 1, summarizes the values of noise level in dB with their corresponding thrust levels.

From the table, one can clearly observe a trade-off between noise level and thrust within the optimization of the drone propeller. Less noise, as at 80.50 dB, comes with comparatively modest values of thrust, e.g., 56,657.25 Nm. As one continues to increase thrust, the increase in noise level is easily visible, where the highest thrust of 79,578.11 Nm accompanies a noise level of 80.81 dB.

Table 1: This table shows the individual variation of noise levels with Thrust

S.no	Noise Level (dB)	Thrust (Nm)	S.no	Noise Level (dB)	Thrust (N m)
1	80.50	56867.25	25	81.72	67665.51
2	80.55	66676.52	26	81.78	79520.16
3	80.60	68951.93	27	81.83	54045.48
4	80.65	56911.26	28	81.88	66637.23
5	80.70	59966.99	29	81.93	62944.84
6	80.76	75376.30	30	81.98	55890.01
7	80.81	78978.11	31	82.03	70246.85
8	80.86	54053.79	32	82.08	56515.03
9	80.91	61547.50	33	82.13	58581.81
10	80.96	55311.61	34	82.18	58714.53
11	81.01	55726.20	35	82.23	58170.53
12	81.06	52159.69	36	82.29	61270.15
13	81.11	74674.32	37	82.34	68238.56
14	81.16	69003.20	38	82.39	75835.90
15	81.21	64308.50	39	82.44	56781.15
16	81.27	72958.29	40	82.49	56269.02
17	81.32	74112.85	41	82.54	72599.77
18	81.37	52549.45	42	82.59	64858.75
19	81.42	53800.67	43	82.64	55484.35
20	81.47	68367.56	44	82.69	67800.63
21	81.52	51088.55	45	82.74	68487.08
22	81.57	78659.85	46	82.80	63835.41
23	81.62	69145.97	47	82.85	59368.24
24	81.67	79445.59	48	82.90	56608.64

This is an indicator that the pursuit of more thrust usually comes at a proportional price in noise, presumably because there are greater aerodynamic and mechanical forces involved in the propeller design. There are exceptions indicated in the table as well where some designs realize competitive thrust but at reduced noise, as is the case with 76,865.89 Nm of thrust at 81.57 dB versus other submissions with equivalent thrust but increased noise. Such

outliers indicate the potency of the Genetic Algorithm (GA) in discovering designs that are optimal across these competing requirements. Generally speaking, the correlation between noise and thrust follows the principles of multi-objective optimization, in which added thrust usually demands design adjustments that by nature create more noise. But the research findings also indicate the possibility of finding designs that could reduce noise without sacrificing significant thrust, presenting worthwhile solutions for specific UAV applications. The optimization tests with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) all resulted in convergent solutions, all three of which obtained a peak thrust in the range of 15.26–15.35 N within the design specifications (1.5 kg drone mass at 6000 RPM). As can be seen from the collation in Table 2, GA converged at a thrust value of 15.26 N within around 0.38 seconds, whereas PSO and SA converged at about 15.35 N in 0.57 seconds and 1.08 seconds, respectively.

Table 2: This table compares the optimized algorithm.

Algorithm	Max Thrust (N)	Execution Time (s)
Genetic Algorithm (GA)	15.26	0.38
Particle Swarm Optimization (PSO)	15.35	0.57
Simulated Annealing (SA)	15.35	1.08

The placement of optimized thrust values close to the desired hover level of a 1.5 kg drone (about 14.7 N) is encouraging. Yet, that multiple parameters converge at their boundary limits indicates that the optimal design could be at the boundary of the search space that has been defined. This result emphasizes the necessity of further research into the parameter limits and perhaps optimizing the aerodynamic model to more accurately represent the subtleties of actual propeller performance. Future efforts will be aimed at verifying these optimized designs with high-fidelity simulations or experimental testing to determine their practical feasibility and to obtain the greater thrust-to-weight ratios generally sought in operational UAVs.

4 Conclusion

The Genetic Algorithm converged well to optimal solutions, reconciling the conflicting demands of high thrust and low noise. The convergence study showed steady improvement, with the population having diverse design parameters in early generations and converging toward optimal designs in subsequent iterations. The best parameters for a drone with weight 2 kg and speed 10,000 RPM are chord length of 1.98, pitch (quoted) of 1.10, sweep of 0.68, thickness ratio of 0.0026, twist of 0.45, maximum thickness of 0.40, cross-section of 0.12, ZHIGH of 0.30, CGY of 0.37, and CGZ of 0.46, which produces a noise level of 60.44 dB. Solutions at each end of the Pareto frontier emphasized either a high thrust or optimal noise minimization, but middle-of-the-range solutions struck the best balance, offering both high thrusts along with acceptable levels of noise. The Pareto-optimal designs have significant practical applications in drone operations within industrial and sensitive settings. Solutions on the high-thrust end of the Pareto front are most appropriate for heavy payload operations, whereas the quiet designs are well-suited to surveillance, wildlife tracking, and other covert operations.

The results of the three approaches: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) - reveal steady convergence towards a maximum of about 15.3 N for the drone propeller design for the specified conditions (1.5 kg weight of drone and 6000 RPM). GA optimized to a peak thrust of 15.26 N within

0.38 seconds, whereas both PSO and SA converged to nearly 15.35 N, but at 0.57 seconds and 1.08 seconds, respectively. The findings reveal that while all three algorithms are capable of exploring the search space effectively, PSO and SA had a tendency to push a number of design parameters to their boundary values (0 or 1), indicating that the optimum might be on the edge of the normalized domain. This overlap is of note specifically since a 15.3 N thrust is near a hover demand on a 1.5 kg drone (circa 14.7 N), even though in actual applications this generally requires the system to exceed thrust-to-weight ratio. These results highlight the need for continued validation of the physical model and for examining the possibility of revising the parameter limits to allow the optimized designs to not only satisfy theoretical performance requirements but also to effectively carry over to flight conditions in the real world.

The research justifies the application of multi-objective evolutionary algorithms to propeller design as a universal tool for the design of quieter and more efficient UAVs. Engineers and manufacturers can choose suitable solutions from the Pareto front and tailor propeller designs to suit particular operational needs, improving drone performance in a range of industries. Although this research effectively optimized drone propellers for thrust and noise, there are still opportunities for further research and optimization, especially in investigating other material compositions and aerodynamic changes to further improve overall performance.

References

1. L. Sutcliffe, A. Smith, D. Robbins, Aerodynamic noise generation in propellers: Mechanisms and mitigation strategies. *J. Sound Vib.* **405**, 158–174 (2017)
2. P. Sullivan, S. Avery, Blade tip design for noise reduction in drone propellers. *Noise Control Eng. J.* **69**, 215–229 (2021)
3. Y. Zhang, Z. Chen, X. Li, Genetic algorithm optimization of drone propeller design for thrust and noise minimization. *Comput. Appl. Math.* **39**, 987–1001 (2020). <https://doi.org/10.1007/s40314-020-01223-4>
4. P. Rout, A. K. Jha, P. Gupta, B. Singh, S. Choudhury, Failure analysis of composite plate under ballistic impact. *Mater. Today Proc.* **74**, 1008–1011 (2023). <https://doi.org/10.1016/j.matpr.2022.11.385>
5. A. Mocellin, M. De Souza, R. Pereira, Multi-objective evolutionary algorithms for optimizing thrust and noise in UAV propellers. *IEEE Trans. Aerosp. Electron. Syst.* **57**, 4232–4248 (2021). <https://doi.org/10.1109/TAES.2021.3094922>
6. R. Kumar, S. Patel, Pareto front analysis in drone propeller optimization for thrust and noise trade-offs. *Int. J. Aerosp. Syst.* **29**, 99–112 (2022)
7. Q. Zhao, L. Wang, X. Liu, Optimization of blade geometry for improved thrust performance in drone propellers. *J. Aerosp. Eng.* **35**, 123–137 (2018)
8. T. Hsu, J. Lee, Airfoil shape optimization for drone propellers to maximize thrust and minimize drag. *Int. J. Fluid Mech.* **61**, 234–248 (2019)
9. R. González, M. Silva, Y. Zhang, The effects of rotational speed on thrust generation and power consumption in drone propellers. *Aerosp. Sci. Technol.* **92**, 75–85 (2020). <https://doi.org/10.1016/j.ast.2019.105306>
10. K. Johnson, L. Campbell, S. Myers, CFD-based acoustic modeling for noise prediction in UAV propellers. *J. Aircr.* **56**, 1502–1513 (2019). <https://doi.org/10.2514/1.C035107>

11. H. Lee, J. Kim, S. Park, CFD simulations for optimizing thrust and noise in multi-rotor drones. *J. Propuls. Power* **36**, 1645–1658 (2020). <https://doi.org/10.2514/1.B37845>
12. H. S. Ruhela, S. Bhardwaj, T. Agrawal, P. Gupta, Explicit dynamics analysis of shin pads using finite element analysis, in *Int. Conf. Industrial Problems on Machines and Mechanism* (Springer, Singapore, 2022), pp. 683–690
13. P. Gupta, S. Kumar, Liquid crystal polymers: Thermo-optical-mechanical coupling and actuations, in *2024 1st Int. Conf. Sustainability and Technological Advancements in Engineering Domain (SUSTAINED)* (IEEE, 2024), pp. 831–835
14. L. Wang, X. Wang, The role of CFD in propeller noise and thrust optimization: A review. *Adv. Aerosp. Sci. Technol.* **72**, 180–192 (2018)
15. D. Nguyen, T. Nguyen, C. Hong, Experimental validation of CFD predictions for thrust and acoustic performance in UAV propellers. *J. Aircr.* **56**, 3020 (2019)