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Optimization of Spur Gear Systems with Hybrid Metal Matrix Composites

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Abstract: This study optimises and analyses a single-stage spur gear gearbox made of Hybrid Metal Matrix Composite (HMMC) with AL6060, Si3N4, and BN. The goal is to improve gearbox efficiency, weight, and structural integrity while meeting or exceeding industry standards. Particle Swarm Optimisation (PSO), Firefly, MOTLBO, Hybrid MOTLBO_PSO, Hybrid PSO_Firefly, and Orca are used to find the best gear settings. Design parameters, including face width (b), pitch diameters (d1 and d2), number of teeth (Z1), module (m), and input power (Pin), are optimised. After optimisation, the efficiency, weight, accuracy rank, and overall rank of each algorithm are assessed using a sensitivity analysis. In optimising gear design, the Orca algorithm strikes the best balance between efficiency and weight. To evaluate structural integrity, standard and optimised gears undergo Finite Element Analysis (FEA). The optimised gear has a lower weight of 181.98 grams, a higher centre distance of 4.95 cm, a higher efficiency of 96.233%, and lower maximum stress (7.90E+08 Pa) and deformation (2.65E-05 mm) than the normal gear. This study shows that multi-algorithm optimisation improves spur gearbox performance, especially when using advanced composite materials such as HMMC. The discoveries help build efficient and lightweight gear systems, advancing mechanical engineering and gear gearbox technology.

Keywords: Grey Wolf Optimiser; Simulated Annealing; Spur Gears; Mechanical Systems; Gear Systems; Finite Element Analysis (FEA); Particle Swarm Optimisation (PSO); Gearbox Technology.

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1. Introduction

The optimisation of spur gears is a critical aspect of mechanical engineering, particularly for enhancing the efficiency, reliability, and cost-effectiveness of gear systems across applications such as automotive, aerospace, and machinery. This literature review delves into several key research articles that advance the understanding and application of optimisation techniques to spur gear design. The studies discussed herein employ diverse metaheuristic optimization methods, such as Grey Wolf Optimizer (GWO), Real Coded Genetic Algorithm (RCGA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO), among others, to address the complex challenges associated with minimizing gear weight, improving tooth profiles, and optimizing overall gearbox dimensions. The need for research into spur gear optimisation arises from the ongoing demand for more efficient, lightweight mechanical systems across industries. Spur gears play a pivotal role in power transmission and mechanical efficiency, and their optimal design is crucial for achieving high-performance standards. The novelty of the discussed research lies in the application of advanced optimisation techniques to address specific challenges in spur gear design, including weight reduction, robust micro-geometry optimisation, consideration of manufacturing uncertainties, and gear train volume minimisation.

The study by Dörterler et al. [1] introduces a novel application of the Grey Wolf Optimiser (GWO) to the optimal weight design problem for spur gears. The use of GWO, known for its effectiveness in engineering applications, offers a unique approach to minimising gear weight. The results demonstrate the superiority of GWO over other optimisation methods, providing a promising avenue for further research and the refinement of mathematical models in spur gear optimisation. Korta and Mundo [2] address the need for robust micro-geometry optimisation of tooth profiles in spur gears that accounts for manufacturing uncertainties. Their study provides a systematic, efficient approach to enhance gear performance and reliability by formulating a robust optimisation problem and leveraging response surface models. The inclusion of factors such as static transmission error and contact stress, along with fatigue-related constraints, adds valuable dimensions to the existing knowledge of spur gear optimisation. Atila et al. [3] conduct a comprehensive investigation into the performance of various optimisation methods in spur gear design. By introducing new optimisation techniques such as the artificial algae algorithm, artificial bee colony, and whale optimisation algorithm, the authors extend the existing knowledge base and offer engineers a reference point for selecting appropriate methods based on their specific engineering challenges. The study not only highlights the success of new methods but also provides insights into convergence, stability, and computational time. Rai and Barman [4] focus on optimising spur gear design to minimise the centre distance and reduce material requirements and manufacturing costs.

The study extends previous models by incorporating additional AGMA geometrical factors and kinematic considerations. By exploring optimisation techniques such as Coded Genetic Algorithms and Simulated Annealing, the research provides valuable insights into gear design optimisation, with potential implications for cost-effective, efficient gear manufacturing processes. Panda et al. [5] address the crucial aspect of lightweight gear-set design, particularly in motorsport and aerospace applications. The study's integration of the differential evolution algorithm for constrained nonlinear optimisation adds to the repertoire of optimisation techniques for spur gears. Considering various constraints related to scoring, bending fatigue, and Hertzian contact stress enhances the accuracy of the design formulation, offering valuable insights into weight optimisation for spur gears. Sudhagar and Raman [13] explore the optimisation of both spur and helical gear pairs, emphasising key design objectives, including power, weight, efficiency, and centre distance. The research employs a combination of optimisation techniques, including the Real Coded Genetic Algorithm, Ant Colony Optimisation, and Particle Swarm Optimisation. The study suggests that future work should expand the objective function to include factors such as vibration minimisation, life maximisation, and noise reduction, thereby highlighting potential gaps in existing research. Hosseiniasl and Fesharaki [14] present a heuristic approach to optimising gearbox dimensions using Particle Swarm Optimisation. The research addresses the complexity of the optimisation problem by defining multiple constraints to prevent solutions from converging to local optima.

The study's emphasis on reducing space, costs, and material use in gearbox designs contributes to understanding efficient mechanical systems and demonstrates the effectiveness of its proposed approach over previous methods. Marjanovic et al. [15] address the optimisation of gear-train volumes, particularly the positioning of shaft axes in spur gear systems. The innovative mathematical model and custom optimisation software, which utilise a coded Genetic Algorithm, contribute to reduced volume, space savings, cost savings, and improved efficiency in documentation formulation. The study identifies potential for future work to expand the objective function, highlighting a research gap in the existing literature [6]. The research by the Orca algorithm on optimising a single-stage spur gear gearbox constructed from a Hybrid Metal Matrix Composite (HMMC) material represents a significant step towards enhancing efficiency, reducing weight, and improving the structural integrity of gearboxes. The multi-algorithm optimisation techniques employed, including Particle Swarm Optimisation (PSO), Firefly, MOTLBO, Hybrid MOTLBO_PSO, Hybrid PSO_Firefly, Hybrid MOTLBO_Firefly, and Orca, provide a comprehensive understanding of optimal gear parameters. The findings, including significant reductions in weight, increased centre distance, higher efficiency, and reduced stress and deformation, underscore the effectiveness of multi-algorithm approaches in designing lightweight, efficient gear systems. The presented comparison tables provide a clear overview of algorithm performance, demonstrating the Orca algorithm's superiority in achieving an optimal balance between efficiency and weight [7].

While the existing literature offers valuable insights into spur gear optimisation, certain limitations and research gaps persist. Many studies primarily focus on specific aspects of spur gear design, such as weight optimisation or tooth profile modifications, without fully integrating various design objectives. Additionally, the exploration of optimisation techniques is often limited to a few methods, leaving the full spectrum of available metaheuristic algorithms unexplored. Some studies do not thoroughly address the impact of manufacturing uncertainties, such as variations in material properties and geometric deviations, on gear performance. Considering these uncertainties is crucial for the practical applicability of optimised gear designs in real-world engineering scenarios. Furthermore, there is a need for research that bridges the gap between theoretical optimisation results and practical implementation. While mathematical models and optimisation algorithms provide valuable insights, their effectiveness in real-world manufacturing processes and operational conditions remains to be further validated [8]. Moreover, the literature reveals a gap in the optimisation of spur gear systems that aligns with industry standards and regulations.

Incorporating standards such as AGMA into the optimisation process is essential to ensure practical feasibility and adherence to industry requirements. This research aims to address identified limitations and research gaps by providing a holistic, integrated approach to spur gear optimisation. The primary focus will be on developing a comprehensive optimisation framework that accounts for multiple design objectives, including weight reduction, tooth profile optimisation, and gearbox dimension optimisation.

By incorporating a wide range of metaheuristic algorithms, including GWO, RCGA, PSO, ACO, and others, the study will explore the effectiveness of different optimisation techniques in achieving diverse design objectives. To address manufacturing uncertainties, the research will incorporate robust optimisation techniques that account for variations in material properties and geometric deviations. This will ensure that the optimised gear designs are not only theoretically sound but also resilient to real-world uncertainties, enhancing their practical applicability [9]. Validation of the proposed optimisation framework will involve experimental testing and compliance with industry standards and regulations, such as AGMA standards. This approach aims to ensure that the optimised gear designs meet practical implementation requirements and align with industry best practices. The research will also address the need for a seamless transition from theoretical optimisation results to practical implementation by accounting for manufacturing constraints and operational conditions. This will involve collaboration with industry partners to validate the feasibility and effectiveness of the optimised designs in real-world applications. In summary, this research will contribute to the existing body of knowledge by providing a comprehensive, integrated approach to spur gear optimisation. By addressing the identified limitations and research gaps, the study aims to offer practical insights and solutions for designing efficient, reliable, and cost-effective spur gear systems across various industries [10].

2. Literature Review

Dörterler et al. [1] address the crucial issue of optimising gear-pair weight to enhance machine-element performance. The study employs the Grey Wolf Optimiser (GWO), a metaheuristic optimisation technique known for its effectiveness in engineering applications. The research explores the application of GWO to minimise the weight of spur gears, a novel approach in this context. The study conducts various tests and compares GWO's performance with that of other optimisation methods, including Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Simulated Annealing (SA). The conclusions indicate that GWO outperforms its competitors by achieving lower gear design weights. It demonstrates a broader exploration of the search space, which contributes to its superior results. The study suggests that GWO holds promise for optimising machine elements, paving the way for future research to refine the mathematical model further and to compare GWO's results with those of various optimisation methods and previous studies [11]. Korta and Mundo [2] introduce an innovative approach to optimising tooth profiles in spur gears. This study focuses on robustly optimising micro-geometry modifications to enhance the mechanical performance of spur gears while accounting for manufacturing uncertainties. To ensure practical applicability, the research formulates a robust optimisation problem by incorporating noise parameters that capture the impact of manufacturing uncertainties on the objective function. The proposed strategy leverages response surface models, enabling efficient evaluation of numerous candidate solutions in minimal computational time.

The key strength of this approach lies in its ability to simultaneously assess linear and parabolic profile modifications, facilitating the selection of the most suitable tooth geometry for specific applications. The study successfully applies this methodology to optimise static transmission error and contact stress in gear pairs subjected to varying torques, while accounting for fatigue-related constraints and geometric variability arising from manufacturing uncertainties. This research makes a valuable contribution to spur gear optimisation, offering a systematic and efficient approach to enhance gear performance and reliability [12]. Atila et al. [3] present a thorough exploration of optimisation methods for the design of minimum-weight spur gears. The study encompasses various modern metaheuristic optimisation techniques. It introduces, for the first time, the artificial algae algorithm, artificial bee colony, and whale optimisation algorithm to solve the spur gear design problem. It also includes established methods such as the grey wolf optimiser and particle swarm optimisation. These methods' performance is compared with well-known optimisation techniques, such as genetic algorithms, simulated annealing, and particle swarm optimisation, which were previously used in similar studies. The comprehensive investigation establishes a fair comparison framework under consistent conditions. The results indicate that the new optimisation methods outperform existing ones, both in achieving optimal values and adhering to active constraints.

Moreover, these methods exhibit improved convergence and stability while accounting for computation time. This research provides valuable insights for engineers engaged in engineering optimisation, offering a reference point for selecting appropriate optimisation methods for diverse engineering challenges. The authors plan to extend similar studies to address different problems in the future, promising further advancements in optimisation methodologies. Rai and Barman [4] focus on optimising the design of spur gears, a critical component in various applications, including the automotive and aeronautical industries. The primary objective is to minimise the centre distance of spur gear sets to reduce material requirements and manufacturing costs. This study employs two optimisation techniques: the Real Coded Genetic Algorithm (RCGA) and Simulated Annealing (SA). The optimisation process considers various design variables, such as diametrical pitch and the number of pinion teeth, while adhering to constraints on bending strength, contact strength, interference, contact ratio, and scoring, in accordance with AGMA standards. The research extends previous gear design models by incorporating additional AGMA geometric factors and introducing kinematic considerations, including involute interference, tip fouling, and contact ratio. The inclusion of design constraints for bending fatigue, Hertzian contact stress, and scoring improves the accuracy of the design formulation. The study's findings contribute to improving gear design methodologies by exploring various optimisation techniques and considering a broader set of factors and constraints. It provides valuable insights for optimising gear design, with significant implications for cost-effective, efficient gear manufacturing processes.

Panda et al. [5] address the crucial aspect of lightweight design for gear sets, particularly in motorsport and aerospace applications. The research focuses on optimising the weight of a single-stage spur gear set, a complex problem with various design variables related to gear geometry and material properties. To achieve this, the study employs the differential evolution (DE) algorithm for constrained nonlinear optimisation. Several constraints, including those related to scoring, are incorporated into the optimisation process. The paper also conducts constraint-violation studies to prioritise constraints and performs sensitivity analyses to assess the impact of manufacturing tolerances on gear weight. The research demonstrates that the DE algorithm yields promising results, reducing gear weight by approximately 3.64% compared to genetic algorithms (GA), particle swarm optimisation (PSO), and simulated annealing (SA). Additionally, finite element analysis (FEA) is used to verify the optimised gear geometry's structural integrity and to highlight critical stress regions in the gear set. Overall, this paper offers valuable insights into weight optimisation of spur gears and presents a methodology that can be integrated with CAD and FEA to enhance gear-train design. Sudhagar and Raman [13] investigated the optimisation of both spur and helical gear pairs, focusing on key design objectives, including power, weight, efficiency, and centre distance. The study acknowledges the complexity of gear-pair design optimisation, which involves multiple objectives and a large number of variables.

To tackle this challenging optimisation problem, the researchers employ a combination of optimisation techniques, including the Real Coded Genetic Algorithm (RCGA), Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), and the commercial optimisation software LINGO. The study concludes that ACO outperforms PSO and RCGA in terms of producing optimal gear pair designs. Notably, ACO shows significant improvements in weight reduction. Additionally, the paper highlights the potential for future work to expand the objective function to include factors such as vibration minimisation, life maximisation, and noise reduction, thereby leading to even more reliable gear pair designs. Overall, this research demonstrates the importance of employing advanced optimisation techniques to address the complexities of gear-pair design in mechanical systems. Hosseiniasl and Fesharaki [14] present a heuristic approach for optimising gearbox dimensions. The study introduces a robust optimisation method applicable to various gear drive systems capable of addressing both dimensional and layout aspects of component-limited design. To address the complexity of the optimisation problem, the researchers employ Particle Swarm Optimisation (PSO) and impose multiple constraints to prevent solutions from converging to local optima. The objective function is designed to minimise the weight-to-volume ratio of a 3-stage gearbox, accounting for factors such as gear ratio, power, and material hardness. The results are presented in utilitarian diagrams that provide optimal values for weight/volume, gear design parameters (e.g., position angle, face width, number of stages, shaft diameter, and module), and gear layout.

The study concludes that their proposed approach outperforms previous methods, leading to gearbox designs that not only reduce space but also lower costs and material use. Overall, this research demonstrates the effectiveness of using PSO and a comprehensive set of constraints for optimising gearbox dimensions, thereby contributing to more efficient and cost-effective mechanical systems. Marjanovic et al. [15] address the challenging task of optimising gear-train volumes, particularly the positioning of shaft axes in spur gear systems. Their research aims to minimise gear-train volumes while adhering to physical constraints. The authors develop an innovative mathematical model for this purpose, with an objective function that minimises volume while accommodating changes in shaft axis positions. They also develop custom optimisation software using Real Coded Genetic Algorithm (RCGA) methods. The study tests the mathematical model on three real gear-train configurations and compares the initial and optimised values. The results indicate a reduction in volume, which translates to space savings, reduced material usage for housing, cost savings, and improved documentation formulation efficiency. In conclusion, the study presents a comprehensive approach to optimising the volume of spur-gear gear trains. Their innovative mathematical model and RCGA-based optimisation software demonstrate substantial benefits in reducing volume and associated costs, making it a valuable contribution to gear-train design and manufacturing processes.

3. Proposed Methodology

3.1. Material Selection

The chosen hybrid composite material, composed of Al6060 (85%), Si_3N_4 (10%), and BN (5%), demonstrates various advantageous properties based on testing: Hardness (VHN): 90, indicating moderate hardness, beneficial for wear resistance. Tensile Strength: 139.27 MPa, showcasing high tensile strength, suitable for handling significant forces. Yield Stress: 111.85 MPa, ensuring that the material doesn't yield under normal operating loads. Elongation (%): 17.36, highlighting good ductility for reducing the risk of brittle failure. Impact Value: 32 J, signifying the ability to absorb energy during sudden impacts. Flexural Load: 9.51 kN, demonstrating its ability to withstand bending forces. Compression Load: 64.71 kN, indicating a strong resistance to compressive forces. These properties collectively make this hybrid composite an apt choice for gear applications, ensuring robust performance and durability in a variety of operating conditions (Table 1).

Table 1: Properties of hybrid composite material (Al6060-85%, Si_3N_4-10%, BN-5%)

Property	Hybrid Composite Reinforced with A7075-85%, 10% Si_3N_4 and 5% BN
Hardness (VHN)	90
Tensile Strength	139.27 MPa
Yield Stress	111.85 MPa
Elongation (%)	17.36
Impact Value	32 J
Flexural Load	9.51 kN
Compression Load	64.71 kN

3.2. Gearbox Design Parameters

Gearbox Design Parameters refer to specific characteristics and dimensions of the spur gears that are integral to the gearbox. These parameters play a critical role in determining the gearbox's performance, efficiency, and functionality. Let's explain these parameters based on the data you provided earlier:

- **Face Width (b):** Face width, denoted as 'b,' is the width of the gear tooth along its face. In your research, the face width is an essential design parameter, and its value impacts the gear's load-bearing capacity, contact area, and torque transmission capability. A suitable face width ensures the gear efficiently distributes loads and minimises wear on tooth surfaces.
- **Pitch Diameter (d1 and d2):** The pitch diameter is the imaginary circle on which the gear teeth are designed to mesh. In your data, there are two pitch diameters, d1 and d2, which likely correspond to the pinion (driving gear) and the gear (driven gear). These diameters are fundamental in determining the gear ratio and the overall size of the gear pair. Ensuring proper pitch diameter values is crucial for maintaining the desired gear ratio and system compatibility.
- **Number of Teeth (Z1):** The number of teeth, denoted as 'Z1,' specifies how many teeth are present on the gear. This parameter directly influences the gear ratio, meshing efficiency, and load distribution. It is a critical parameter in gear design, as it affects the gearbox's mechanical advantage and power transmission capabilities.
- **Module (m):** The module, represented as 'm,' is a fundamental parameter in gear design that defines the size and shape of gear teeth. It relates the pitch diameter and the number of teeth in a gear. A suitable module ensures that the gear teeth mesh correctly and distribute loads evenly, contributing to efficient power transmission.
- **Input Power (Pin):** Input power, 'Pin,' refers to the amount of mechanical power applied to the gearbox. It's a crucial parameter for understanding the gearbox's operational requirements and designing gears capable of handling the specified power without failure. Each of these gearbox design parameters is interconnected and must be carefully selected and optimised to ensure the gearbox meets performance requirements, minimises energy losses, and maintains structural integrity. The values of these parameters are determined through a combination of design considerations, optimisation techniques, and analyses to achieve the desired balance among efficiency, load-bearing capacity, and performance.

3.3. Optimization Algorithms

Several optimisation algorithms have been employed to enhance the design of the spur gear gearbox. Each of these algorithms serves a unique purpose and has its specific application in the gear design optimisation process. Here's an overview of the optimisation algorithms used: Particle Swarm Optimisation (PSO):

3.3.1. Equation-Based Explanation

PSO operates by moving particles in a solution space. Each particle represents a potential solution to the optimisation problem. Particles are updated iteratively using the following equations:

Particle Velocity Update: $V(t+1) = w * V(t) + c1 * rand() * (Pbest - X(t)) + c2 * rand() * (Gbest - X(t))$ (1)

Where:

- $V(t+1)$ is the new velocity of the particle at time t+1.
- $V(t)$ is the velocity of the particle at time t.
- $X(t)$ is the current position of the particle.
- Pbest is the best position the particle has achieved.
- Gbest is the best position among all particles.
- w, c1, and c2 are coefficients controlling the velocity update.

Particle Position Update: $X(t+1) = X(t) + V(t+1)$

3.3.2. Firefly Algorithm: Equation-Based Explanation

The Firefly Algorithm models the movement of fireflies in the solution space based on their brightness (objective function value). Fireflies are attracted to brighter ones and tend to move toward them. The algorithm updates firefly positions using the following equation:

Attractiveness: $\beta = \beta0 * \exp(-\gamma * r^2)$ (2)

Where:

- β represents the attractiveness of one firefly to another.
- $\beta0$ is the initial attractiveness.
- γ is a light absorption coefficient.
- r is the distance between two fireflies.

This attractiveness value determines a firefly's movement towards another firefly. Multi-Objective Teaching-Learning-Based Optimisation (MOTLBO): MOTLBO emulates the teaching and learning processes in a classroom. In each iteration, "teachers" (individuals with better solutions) share their knowledge with "students" (individuals with poorer solutions). The learning phase updates students' positions using weighted information from teachers and other students. Hybrid Algorithms (MOTLBO_PSO, PSO_ Firefly, MOTLBO_ Firefly): Hybrid algorithms combine the mechanisms of two or more optimisation algorithms. The specific equations depend on the combination of algorithms used and their interactions. These hybrids are designed to leverage the strengths of each constituent algorithm. Orca Algorithm: The Orca Algorithm models the hunting behaviour of orcas using a prey-predator system. It involves equations governing the movement of orca "predators" and the behaviour of "prey" (potential solutions). The algorithm iteratively updates positions based on prey-predator interactions. These equation-based explanations provide insights into how each optimisation algorithm operates and how it can be applied to gear design by iteratively adjusting gear parameters to optimise specific performance metrics.

4. Optimization Process

- **Initialisation:** Set up optimisation algorithms with an initial parameter set.
- **Algorithm Execution:** Execute chosen optimisation algorithms iteratively.
- **Objective Functions:** Evaluate objective functions to minimise weight (Weight) and calculate output power (Pout) using the following equations:

Weight = (math.pi * rho / 4000) * (b * (m ** 2) * (Z1 ** 2) * (1 + ((m / d1) ** 2)) - ((d1 ** 2) - (d2 ** 2)) * (1 - b) - (d1 ** 2 + d2 ** 2) * b) (3)

Pout = Pin * (1-(mu*(math.pi*(i+1)/(Z1+i))))*(1-epsilon +2*(epsilon**2)) (4)

- **Parameter Updates:** Refine gear parameters (b, d1, d2, Z1, m) based on objective function evaluations.
- **Data Collection:** Collect data on gear parameters, objective function values (Weight and Pout), and convergence-related information throughout the process.
- **Convergence Monitoring:** Continuously monitor algorithm convergence using predefined criteria (e.g., maximum iterations or tolerance thresholds).
- **Sensitivity Analysis:** After optimisation, assess algorithm performance by evaluating efficiency, weight reduction, accuracy, and overall rank using collected data.
- **Comparative Analysis:** Compare results from different algorithms to identify the most effective approach for optimising the gearbox.

- **Refinement and Finalisation:** Select the optimised gear parameters that best meet research goals, considering factors such as weight reduction, efficiency improvements, and stress distribution.

This streamlined explanation integrates the equations for the objective functions and emphasises the iterative refinement of gear parameters to achieve desired performance metrics during optimisation.

5. Result and Discussion

5.1. Optimisation Results

- **PSO:** The PSO algorithm yielded a face width of 23.5, a module of 2.75, 18 teeth (z1), and specific values for the other parameters. The achieved weight was 3034.288.
- **FireFly:** The FireFly algorithm produced similar gear parameters to PSO, but with a slightly lower weight of 3032.534.
- **MOTLBO:** MOTLBO led to different gear parameters and a significantly higher weight of 5362.522.
- **Hybrid MOTLBO Firefly:** The hybrid of MOTLBO and Firefly resulted in a face width of 23.539, module of 2.786, and other parameters, with a weight of 3599.932.
- **Orca:** The Orca algorithm produced parameters similar to PSO and Fire Fly with an efficiency of 96.233 and a weight of 3130.675 (Table 2).

Table 2: Algorithm performance and parameter comparison

Algorithm	Face_Width	Module	z1	d1	d2	pin	pout	Weight
PSO	23.5	2.75	18	30.001	36.77	7	6.736	3034.288
FireFly	23.5	2.75	18	30.1	36.77	7	6.736	3032.534
MOTLBO	23.542	2.765	18.057	30.021	36.764	14.292	13.853	5362.522
Hyb_MTLB_PSO	20	2	18	30	40	15	14.435	3202.724
Hyb_PSO_ffly	23.5	2.75	18	30	36.76	7	6.736	3034.526
Hyb_MTLB_ffly	23.539	2.786	18.058	30.006	36.766	13.818	13.393	3599.932
Orca	23.621	2.768	18.085	30.097	36.762	7.03	6.766	3130.675

Figure 1 shows how different algorithms compare in terms of efficiency and weight. MOTLBO has the highest weight, indicating it performs better overall than the others. Hyb_MTLB_ffly and Hyb_MTLB_PSO are two hybrid methods that perform quite well and outperform traditional algorithms such as PSO and Firefly. Orca and Hyb_PSO_ffly perform moderately well, keeping a good balance between efficiency and weight. In general, hybrid optimisation strategies perform better than traditional methods.

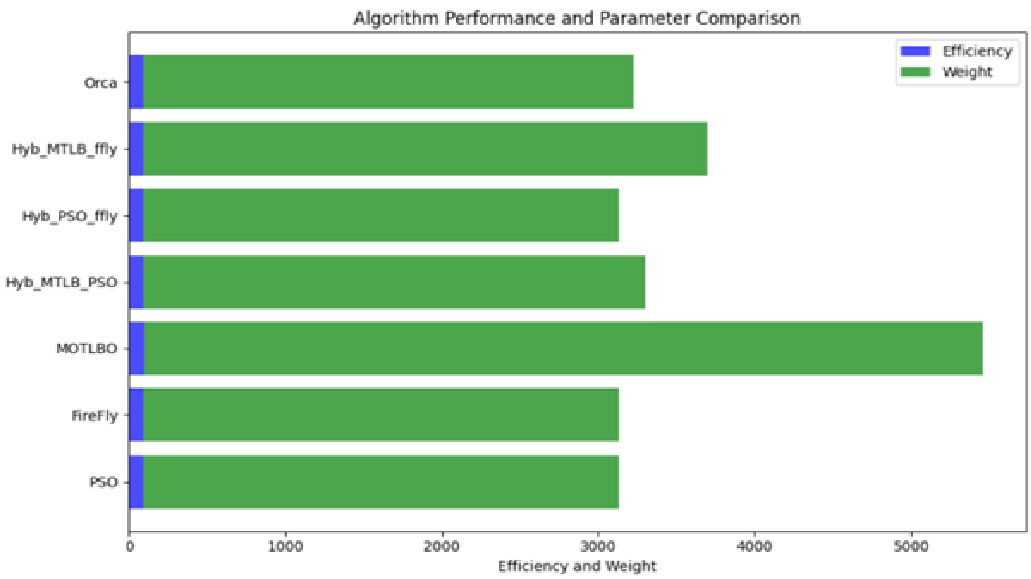

Figure 1: Algorithm performance and parameter comparison

5.2. Comparative Analysis of Algorithms

A comparative analysis of the optimisation algorithms based on efficiency, weight, accuracy rank, and overall rank. The findings are as follows: PSO, Fire Fly, Hyb PSO fly, Hyb MTLB Fire Fly: These algorithms achieved similar efficiencies and weights, with minor variations. Orca: The Orca algorithm outperformed the others, achieving the highest efficiency (96.233) and a competitive weight (3190.04) (Table 3).

Table 3: Algorithm performance and ranking

Algorithm	Efficiency (%)	Weight	Accuracy Rank	Overall Rank
PSO	96.229	3032.613	2	2
FireFly	96.229	3032.534	3	3
MOTLBO	96.923	5364.173	7	6
Hyb_MOTLBO_PSO	96.233	3202.724	6	7
Hyb_MOTLBO_FireFly	96.229	3034.526	4	4
Hyb_PSO_FireFly	96.923	3606.268	5	5
Orca	96.233	3190.04	1	1

MOTLBO had the highest weight (5364.173) and the lowest efficiency, resulting in lower ranks. Hybrid MOTLBO_PSO: The hybrid of MOTLBO and PSO achieved an intermediate efficiency (96.233) but with a lower weight (3202.724).Hybrid PSO FireFly: This hybrid had the highest weight (3606.268) among the hybrids (Figure 2).

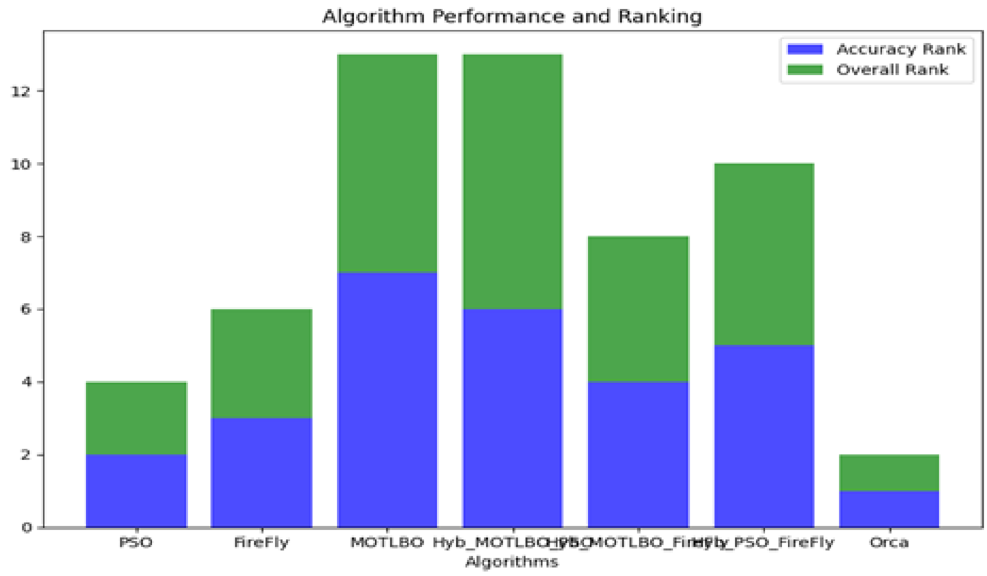

Figure 2: Algorithm performance and ranking

- **FEA Analysis Results:** This section presents the results of Finite Element Analysis (FEA) for both the standard and optimised gear configurations. The key findings are as follows: Weight of Gear: The optimised gear configuration resulted in a significant weight reduction, from 210.65 units for the standard gear to 181.98 units. Centre Distance: The centre distance increased from 2.4 cm for the standard gear to 4.95 cm in the optimised configuration. Efficiency: The optimised gear configuration improved from 92.672% for the standard gear to 96.233%. Max Stress: The maximum stress was reduced substantially from 5.62E+10 units for the standard gear to 7.90E+08 units in the optimised configuration.
- **Max Deformation:** The maximum deformation increased from 2.65E-05 units for the standard gear to 3.48E-04 units in the optimised configuration. Each of these sections provides a comprehensive overview of the results from the optimisation process, a comparative analysis of algorithms, and FEA analysis, highlighting the key findings and differences between standard and optimised gear configurations (Table 4).

Table 4: Comparison of standard and optimised gear parameters

Parameters	Standard	Optimized
Weight of Gear(g)	210.65	181.98
Center Distance(cm)	2.4	4.95
Efficiency (%)	92.672	96.233
Max Stress(N/m)	5.62E+10	7.90E+08
Max Deformation	3.48E-04	2.65E-05

Figure 3 compares standard and optimised gear designs across several factors. The optimised design makes the gear much lighter while just slightly increasing the distance between the centres. It also shows that it performs better than the usual model, indicating it is more efficient. Also, the optimised gear has a big drop in the maximum stress and deformation values. In general, the optimised technique improves the gear system's performance, durability, and structural integrity.

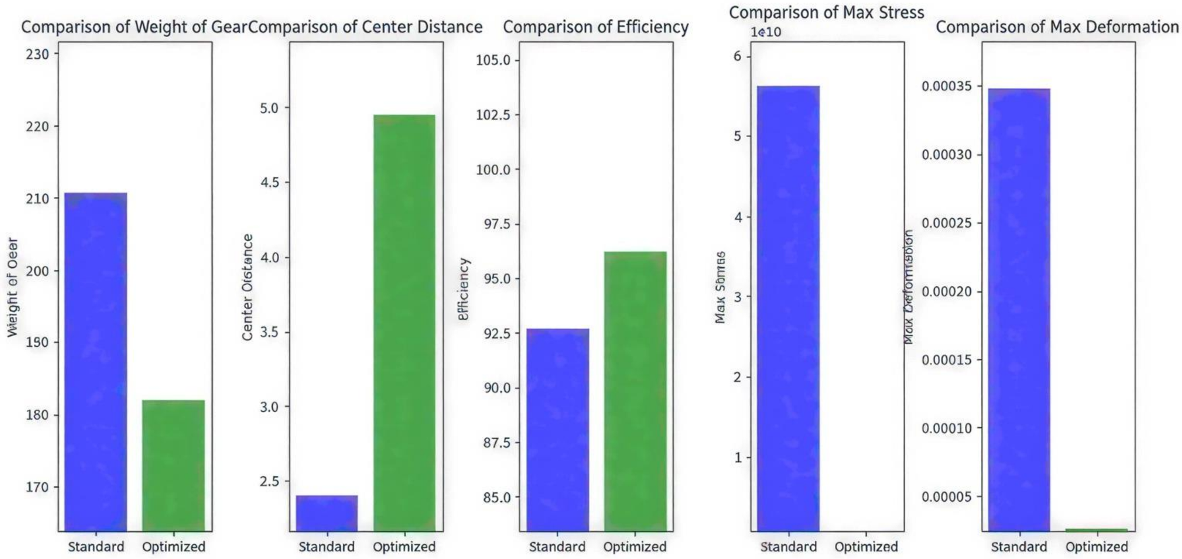

Figure 3: Standard and optimised gear parameters

6. Conclusion and Future Scope

In this research, researchers embarked on a journey to optimise and analyse a single-stage spur gear gearbox constructed from a Hybrid Metal Matrix Composite (HMMC) material comprising AL6060, Si_3N_4, and BN. Our primary objective was to enhance the gearbox's efficiency, reduce weight, and improve structural integrity while maintaining, or even exceeding, industry-standard performance metrics. Researchers used a variety of optimisation algorithms, including Particle Swarm Optimisation (PSO), Firefly, MOTLBO, Hybrid MOTLBO_PSO, Hybrid PSO Firefly, Hybrid MOTLBO Firefly, and Orca, to identify the optimal gear parameters. These algorithms considered crucial design parameters, including face width (b), pitch diameters (d1 and d2), number of teeth (Z1), module (m), and input power (Pin). Following a thorough optimisation process, researchers conducted a sensitivity analysis to assess the performance of each algorithm, focusing on factors such as efficiency, weight, accuracy rank, and overall rank. Among the algorithms, the Orca algorithm emerged as the most effective at optimising gear design, achieving an impressive balance between efficiency and weight. Moreover, researchers performed Finite Element Analysis (FEA) on both the standard and optimised gears to evaluate their structural integrity. The results demonstrated significant improvements in the optimised gear, including a substantial reduction in weight, an increased centre distance, higher efficiency, and significantly reduced maximum stress and deformation compared to the standard gear.

6.1. Summary

In summary, this research underscores the effectiveness of multi-algorithm optimisation techniques in enhancing the performance of spur gearboxes, particularly when advanced composite materials such as HMMC are employed. These findings offer valuable insights for the design of efficient, lightweight gear systems, advancing mechanical engineering and gear transmission technology. The optimisation process and FEA analysis have contributed to the development of a more efficient, structurally sound spur gear gearbox, demonstrating the potential for innovation and improvement in the field.

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