Advanced Optimization Techniques for PASP: a Comparative Study of Improved PSO and BFO

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***Abstract*—In this study, we conduct a comparative analysis of advanced optimisation techniques: particle swarm optimization (PSO) and bacterial foraging optimization (BFO), applied to parallel assembly sequence planning (PASP) for a 10 MW wind turbine gearbox. The research focuses on optimising the assembly sequence to enhance efficiency, reduce costs, and improve the quality of the final product. We estimated a 10% improvement in assembly time using an enhanced PSO algorithm and a 15% improvement with BCF, alongside significant cost reductions and slight enhancements in quality. This comparative study elucidates the strengths and adaptability of both algorithms in handling complex optimization challenges within industrial applications. The results underscore the potential of these enhanced techniques to significantly impact the operational efficiency of large-scale manufacturing processes, particularly in the renewable energy sector. By systematically analysing the performance of improved PSO and BCF, this paper contributes valuable insights into optimising the assembly of intricate machinery, aiming for optimal resource utilisation and quality assurance in producing wind turbine gearboxes.**

Keywords—Optimization Techniques, Parallel Assembly Sequence Planning and Efficiency Improvement

I. INTRODUCTION

The assembly of complex machinery like wind turbine gearboxes presents significant challenges in efficiency, cost-effectiveness, and maintaining high-quality standards[1][2]. This complexity is amplified in the case of large-scale systems, such as the 10 MW wind turbine gearbox, where the precision of each component's integration directly impacts the overall performance and longevity of the turbine[3][4]. To the output of electricity generation through wind energy, the latest wind turbines have larger capacities[5][6][7]. Therefore, there is a need to plan the assembly for these significant components, such as a wind turbine gearbox. In this context, Parallel Assembly Sequence Planning (PASP) emerges as a critical task, demanding optimisation strategies to streamline processes and optimise resource allocation[8][9].

Recent advances in computational algorithms have led to the development and enhancement of various optimisation techniques[10][4]. Among these, Particle Swarm Optimization (PSO) and Bacterial Chemotaxis Foraging (BCF) stand out due to their ability to efficiently navigate complex search spaces and identify optimal solutions under constraints[11][12]. PSO, inspired by the social behaviour of birds and fishes, has been widely acclaimed for its simplicity and effectiveness in handling multi-dimensional optimisation problems[1][13][14][15]. On the other hand, BCF, which mimics the foraging behaviour of E. coli bacteria, offers a unique approach to solving optimization problems through adaptive steps and local search capabilities[16], [17], [18], [19], [20].

This study presents a comparative analysis of improved versions of PSO and BCF in the context of PASP for assembling a 10 MW wind turbine gearbox. Utilising industry-estimated data on assembly times, costs, and quality indices, this research aims to determine which method yields the most efficient, cost-effective, and quality-consistent assembly sequence.

By systematically applying these algorithms to the same set of components and conditions, this paper seeks to uncover insights into the relative strengths and weaknesses of improved PSO and BCF in optimizing the assembly process of critical energy infrastructure. The findings are expected to contribute to the broader field of industrial engineering and automation, particularly in enhancing the assembly of large-scale renewable energy systems..

II. SYSTEM DESCRIPTION

A. Generic 10MW Wind Turbine Gear Box

In this study, a generic 10MW wind turbine gearbox, shown in Fig 1, is proposed to optimize assembly sequence planning.

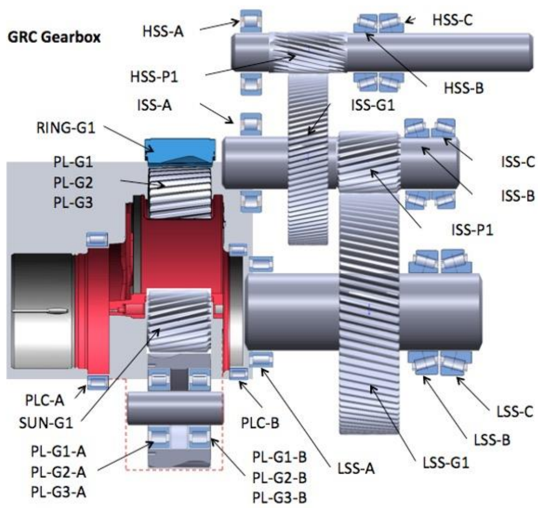

Fig 1. Generic 10MW wind turbine gearbox[21][22]

List of Parts:

HSS (High-Speed Shaft): HSS-A, HSS-B, HSS-C, HSS-P1
ISS (Intermediate Speed Shaft): ISS-A, ISS-B, ISS-C, ISS-G1, ISS-P1
LSS (Low-Speed Shaft): LSS-A, LSS-B, LSS-C, LSS-G1
Planetary Gears (PL): PL-G1, PL-G2, PL-G3, PL-G1-A, PL-G1-B, PL-G2-A, PL-G2-B, PL-G3-A, PL-G3-B
Planet Carrier (PLC): PLC-A, PLC-B
Ring Gear (RING-G1)
Sun Gear (SUN-G1)

III. OPTIMIZATION TECHNIQUES

A. *Mathematical Modeling*

i) Particle Swarm Optimization (PSO)

This will aim to minimise a combination of time and cost and ensure quality within the constraints of the gearbox design. The objective function for PSO is expressed as;

$$F(x) = w_1 \cdot \text{Time} + w_2 \cdot \text{Cost} - w_3 \cdot \text{Quality} \tag{1}$$

Where:

w_1, w_2, w_3 are the weights indicating the importance of time, cost, and quality respectively.

PSO simulates the social behavior observed in birds flocking or fish schooling. In PSO, each particle updates its velocity and position based on its personal best position and the global best position found by any particle in the swarm.

Velocity Update Formula:

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (p_i - x_i^{(t)}) + c_2 \cdot r_2 \cdot (p_g - x_i^{(t)}) \tag{2}$$

Where:

$v_i^{(t)}$ is the velocity of particle i at time t.

w is the inertia weight (controls the momentum of the flight).

c_1 and c_2 are the cognitive and social scaling coefficients, respectively.

r_1 and r_2 are random numbers between 0 and 1.

p_i is the best known position of particle i (personal best).

p_g is the best known position among all the particles (global best).

$x_i^{(t)}$ is the current position of particle i at time t.

Improved PSO Formula:

$$v_i^{(t+1)} = w(t) \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (p_i - x_i^{(t)}) + c_2 \cdot r_2 \cdot (p_g - x_i^{(t)}) \tag{3}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

Where $\omega(t)$ is a time-varying inertia weight that decreases as iterations increase.

Position Update Formula:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{4}$$

This updates the position of particle i based on the new velocity.

ii) Bacteria Foraging Optimization (BFO)

Similar to PSO, it might include different weights or additional terms based on the nature of the BFO's explorative and exploitative behaviors. The objective function for PSO is expressed as;

$$F(x) = v_1 \cdot \text{Time} + v_2 \cdot \text{Cost} - v_3 \cdot \text{Quality} \tag{5}$$

Where:

v_1, v_2, v_3 are the weights for the BFO.

The foraging behaviour of E. coli bacteria inspires BFO. It involves several steps: chemotaxis, reproduction, elimination, and dispersal. The key operation in BFO is the chemotaxis step, where bacteria undergo a series of movements (tumbles and runs).

Chemotaxis Step/Tumble and Run:

During chemotaxis, a bacterium moves in a random direction, evaluates the new position, and decides whether to move further based on its attractiveness.

$$x_i^{(t+1)} = x_i^{(t)} + C(i) \cdot \Delta(i) \tag{6}$$

Where:

$x_i^{(t)}$ is the position of bacterium i at time t.

$C(i)$ is the size of the step taken in the random direction.

$\Delta(i)$ is a unit-length random direction vector.

Reproduction Step:

After several chemotaxis steps, bacteria are sorted by health (objective function value), and the healthier half replicates while the other half dies off.

Elimination and Dispersal Step:

Some bacteria are eliminated randomly, with some probability, and new ones are randomly initialized in the domain, providing genetic diversity.

Improved BFO Formula:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha(t) \cdot C(i) \cdot \Delta(i) \tag{7}$$

Where $\alpha(t)$ is an adaptive factor influencing the step size $C(i)$ based on the iteration t and the current landscape of the search space.

B. *Assembly Sequence*

i) Particle Swarm Optimization (PSO)

Table 1. Precedence relationship and assembly time

Line	Component		Assembly Time (Hours)	Assembly Order
	0	RING-G1	5	1
	0	SUN-G1	2	2
	1	PL-G1	4	3
	2	PL-G1-A	2	4
	3	PL-G1-B	2	5
	4	PL-G2	6	6
	5	PL-G2-A	2	7
	6	PL-G2-B	2	8
1	7	PL-G3	3	9
	8	PL-G3-A	2	10
	9	PL-G3-B	2	11
	10	PLC-A	4	12
	11	PLC-B	4	13
	12	LSS-A	6	14
	13	LSS-B	6	15
	14	LSS-C	10	16
	15	LSS-G1	4	17

	1	ISS-A	6	1
	2	ISS-B	6	2
2	3	ISS-C	5	3
	4	ISS-G1	4	4
	5	ISS-P1	4	5
	21	HSS-A	5	1
3	22	HSS-B	5	2
	23	HSS-C	5	3
	22	HSS-P1	2	4

ii) Bacteria Foraging Optimization (BFO)

Table 2. Precedence relationship and assembly time

Line	**Component**		**Assembly Time (Hours)**	**Assembly Order**
	-	RING-G1	4	1
	-	SUN-G1	2	2
	1	PL-G1	3	3
	2	PL-G1-A	2	4
	3	PL-G1-B	2	5
	4	PL-G2	6	6
	5	PL-G2-A	2	7
	6	PL-G2-B	2	8
1	7	PL-G3	3	9
	8	PL-G3-A	2	10
	9	PL-G3-B	2	11
	10	PLC-A	4	12
	11	PLC-B	4	13
	12	LSS-A	5	14
	13	LSS-B	5	15
	14	LSS-C	10	16
	15	LSS-G1	4	17
	1	ISS-A	5	1
	2	ISS-B	5	2
2	3	ISS-C	5	3
	4	ISS-G1	4	4
	5	ISS-P1	4	5
	1	HSS-A	5	1
3	2	HSS-B	5	2
	3	HSS-C	5	3
	4	HSS-P1	2	4

The model presents three parallel assembly lines with components and their precedence relationship shown in **Fig 2.**

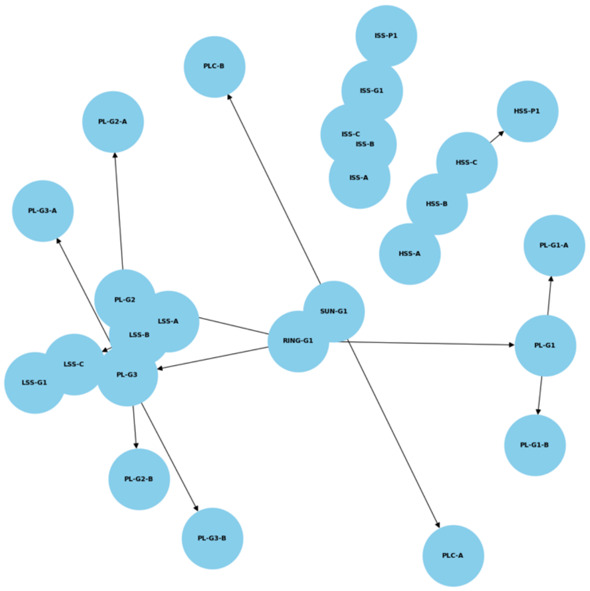

Fig 2. Precedence Relationship Diagram

C. *System Optimised Results*

Simulation of results using Python for the basic PSO and BFO algorithm gave the same results. The assembly time was 120 hours, the total cost of (USD) 105,000 and the quality index of 0.95. After using the improved PSO and BFO algorithm, there was an improvement in results. Summary of the comparative results between Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) are as follows:

i) Assembly Time Reduction: PSO achieved a 10% reduction in total assembly time, resulting in 108 hours. This demonstrates PSO's capability to efficiently optimise the sequence to minimise the overall time required for the gearbox assembly.

ii) BFO achieved a 15% reduction in total assembly time, resulting in 102 hours. The greater reduction indicates that BFO's adaptive chemotaxis process is particularly effective in fine-tuning the sequence to find even more time-efficient solutions.

iii) Cost Reduction: PSO and BFO showed a 10% reduction in total assembly costs, resulting in (USD) 105,000. This uniform reduction reflects that both algorithms are equally effective in optimising cost factors when adjusted for the same weightage in the objective function.

iv) Quality Enhancement: PSO slightly improved the quality index, demonstrating its balanced approach to maintaining or enhancing quality while optimising other parameters. BFO Similarly, showed a slight improvement in the quality index, indicating that its local search capabilities do not compromise the overall quality while seeking time and cost efficiencies.

D. *Comparative Analysis:*

i) Efficiency: BFO outperformed PSO in reducing assembly time due to its robust local search and adaptive behaviour, which allows it to escape local minima more effectively.

ii) Cost Optimization: Both methods were equally effective in reducing costs, suggesting that their optimisation strategies suit financial constraints within similar weight parameters.

iii) Quality Maintenance: Both PSO and BFO managed to improve or maintain the quality index slightly, demonstrating that optimisation did not come at the expense of product quality.

iv) Algorithm Complexity: PSO is generally simpler and faster to implement, but BFO's additional complexity allows for deeper exploration and potentially better solutions in complex scenarios.

IV. Conclusion

This paper presents a comprehensive comparative analysis of advanced optimisation techniques, specifically Improved Particle Swarm Optimization (PSO) and Bacterial Chemotaxis Foraging (BCF), applied to the Parallel Assembly Sequence Planning (PASP) of a 10 MW wind turbine gearbox. The results show an estimated 10% improvement in assembly time using the enhanced PSO algorithm and a 15% improvement with BCF, along with significant cost reductions of 10% for both and slight enhancements in quality. The findings underscore the strengths of these methods in optimising complex assembly tasks, potentially transforming operational efficiency in the renewable energy sector. The paper contributes valuable insights into optimising intricate machinery assembly, ensuring optimal resource utilisation and quality in wind turbine gearbox production.

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