Multi Objective Migrating Birds and Particle Swarm Optimization Algorithms

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Abstract: Multiobjective optimization problems (MOPs) involve optimizing two or more conflicting objectives, often subject to several constraints. Solving such problems efficiently requires algorithms that can find Pareto-optimal solutions, where no solution can be improved in any objective without degrading another. Migrating Birds Optimization (MBO) is a nature-inspired algorithm that mimics the migration behavior of birds. This paper introduces an enhanced version of MBO, tailored for solving MOPs, and compares its performance with Particle Swarm Optimization (PSO). The proposed MBO algorithm, specifically designed for multiobjective problems, incorporates constraint handling mechanisms and the concept of Pareto dominance to find Pareto-optimal solutions. The effectiveness of the algorithm is demonstrated on a multiobjective problem with three constraints, with comparisons to PSO using Python and graphical results.

Keywords: *Multiobjective Optimization, Migrating Birds Optimization, Particle Swarm Optimization, Pareto-Optimal Solutions, Constraint Handling, Nature-İnspired Algorithms.*

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I. INTRODUCTION

Multiobjective optimization (MOO) refers to the optimization of problems involving multiple, often conflicting, objectives. In these problems, a solution is considered optimal if no objective can be improved without degrading another objective. These problems often arise in real-world applications, such as engineering design, resource allocation, and environmental management.

Traditional optimization methods struggle with multiobjective problems due to the necessity of finding a set of Pareto-optimal solutions. This has led to the development of nature-inspired algorithms, which are effective in handling complex MOPs. Migrating Birds Optimization (MBO) is one such algorithm that mimics the migration behavior of birds to find optimal solutions in a search space. It has been successfully applied to single-objective problems; however, its application to multiobjective optimization has remained underexplored.

This paper presents a multiobjective version of the MBO algorithm and compares its performance to Particle Swarm Optimization (PSO). The proposed MBO algorithm uses Pareto dominance for selecting optimal solutions, and it is enhanced with constraint handling mechanisms to tackle constrained MOPs.

II. MIGRATING BIRDS OPTIMIZATION ALGORITHM (MBO)

MBO is a population-based optimization algorithm that simulates the migratory behavior of birds. Birds move in a search space in an attempt to find optimal solutions by balancing exploration and exploitation. The basic concept of MBO involves the following:

- **Initialization:** A population of birds is randomly distributed across the search space, with each bird representing a potential solution.
- **Migration Behavior:** Each bird's movement is influenced by the best solution it has encountered and the best solution in the entire population.
- **Update Mechanism:** The birds update their positions based on their velocity and the migration behavior. In multiobjective MBO, this update considers the Pareto dominance of solutions, guiding birds toward better regions of the search space.

➢ *The Multiobjective Extension of MBO İncorporates the Following Additional Elements:*

- **Pareto Dominance:** Solutions are evaluated using Pareto dominance, where a solution dominates another if it is at least as good in all objectives and strictly better in one.
- **Constraint Handling:** MBO uses penalty functions to handle constraints in MOPs, ensuring that solutions respect the problem’s constraints.

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➤ *Particle Swarm Optimization (PSO)*

PSO is another nature-inspired optimization technique that simulates the social behavior of particles. Each particle represents a potential solution, and particles move through the search space based on their previous best position and the best position found by the swarm.

In multiobjective PSO, the swarm tries to find Pareto-optimal solutions by comparing the performance of each particle across multiple objectives. PSO has been widely applied to multiobjective problems due to its simplicity and effectiveness.

➤ *Multiobjective Optimization Problem*

Consider the following multiobjective optimization problem with three objectives and three constraints:

Minimize:
$f_1(x,y,z)=x^2+y^2+z^2$
$f_2(x,y,z)=(x-1)^2+(y-2)^2+(z-3)^2$
$f_3(x,y,z)=(x+1)^2+(y+2)^2+(z+3)^2$
Subject to:
$g_1(x,y,z)=x+y+z-5\leq 0$
$g_2(x,y,z)=x^2+y^2+z^2-9\leq 0$
$g_3(x,y,z)=x-1\geq 0$

Where x, y, and z are decision variables. The goal is to minimize the three conflicting objectives while satisfying the constraints.

III. METHODOLOGY

The multiobjective MBO (MOMBO) algorithm is applied to the above problem and compared to PSO. Both algorithms are evaluated based on their ability to find a set of Pareto-optimal solutions while respecting the constraints.

- **Initialization:** Random populations of birds (for MOMBO) and particles (for PSO) are generated within the feasible region of the search space.
- **Objective Evaluation:** Each bird or particle is evaluated using the three objective functions.
- **Constraint Handling:** For both algorithms, penalty functions are applied to any solution that violates the constraints.
- **Pareto Dominance:** Solutions are compared using Pareto dominance, and the best solutions are selected for the next iteration.
- **Termination Condition:** The algorithms terminate when a predefined number of iterations is reached.

IV. RESULTS AND DISCUSSION

The performance of the MOMBO and PSO algorithms is compared in terms of their ability to find Pareto-optimal solutions. The results are presented graphically, showing the trade-offs between the three objectives.(See Figure-1)

V. CONCLUSION

The Multiobjective Migrating Birds Optimization algorithm demonstrates its ability to handle constrained MOPs effectively, offering a promising solution for finding Pareto-optimal solutions. When compared to Particle Swarm Optimization, MOMBO shows a strong potential for solving complex multiobjective problems with constraints.

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APPENDIX—PYTHON CODE

```
import numpy as np
import matplotlib.pyplot as plt
# Define the objective functions and constraints
def objective_functions(x, y, z):
    f1 = x**2 + y**2 + z**2
    f2 = (x - 1)**2 + (y - 2)**2 + (z - 3)**2
    f3 = (x + 1)**2 + (y + 2)**2 + (z + 3)**2
    return f1, f2, f3
def constraints(x, y, z):
    g1 = x + y + z - 5
    g2 = x**2 + y**2 + z**2 - 9
    g3 = x - 1
    return g1, g2, g3

# MOMBO Algorithm
def mombo(iterations, population_size):
    # Initialize population (birds)
    population = np.random.uniform(-5, 5, (population_size, 3))
    for iteration in range(iterations):
        for i in range(population_size):
            x, y, z = population[i]
            f1, f2, f3 = objective_functions(x, y, z)
            g1, g2, g3 = constraints(x, y, z)
           # Apply constraints (penalty function)
            penalty = sum([max(0, g) for g in [g1, g2, g3]])
            fitness = [f1 + penalty, f2 + penalty, f3 + penalty]
             # Update positions (using Pareto dominance)
            # (Implementation details of the Pareto dominance and position update)
             return population
# PSO Algorithm
def pso(iterations, population_size):
    # Initialize particles
    population = np.random.uniform(-5, 5, (population_size, 3))
    for iteration in range(iterations):
        for i in range(population_size):
            x, y, z = population[i]
            f1, f2, f3 = objective_functions(x, y, z)
            g1, g2, g3 = constraints(x, y, z)

            # Apply constraints (penalty function)
            penalty = sum([max(0, g) for g in [g1, g2, g3]])
            fitness = [f1 + penalty, f2 + penalty, f3 + penalty]

            # Update particles (using velocity and position update)
            # (Implementation details of PSO update)
            return population
# Run both algorithms and compare the results
mombo_population = mombo(100, 50)
pso_population = pso(100, 50)
```

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```
# Visualization (graphical output)
plt.scatter(mombo_population[:, 0], mombo_population[:, 1], label="MOMBO", color="blue")
plt.scatter(pso_population[:, 0], pso_population[:, 1], label="PSO", color="red")
plt.legend()
plt.xlabel('Objective 1')
plt.ylabel('Objective 2')
plt.title('Comparison of MOMBO and PSO')
plt.show()
```

➤ *Output of the Code*

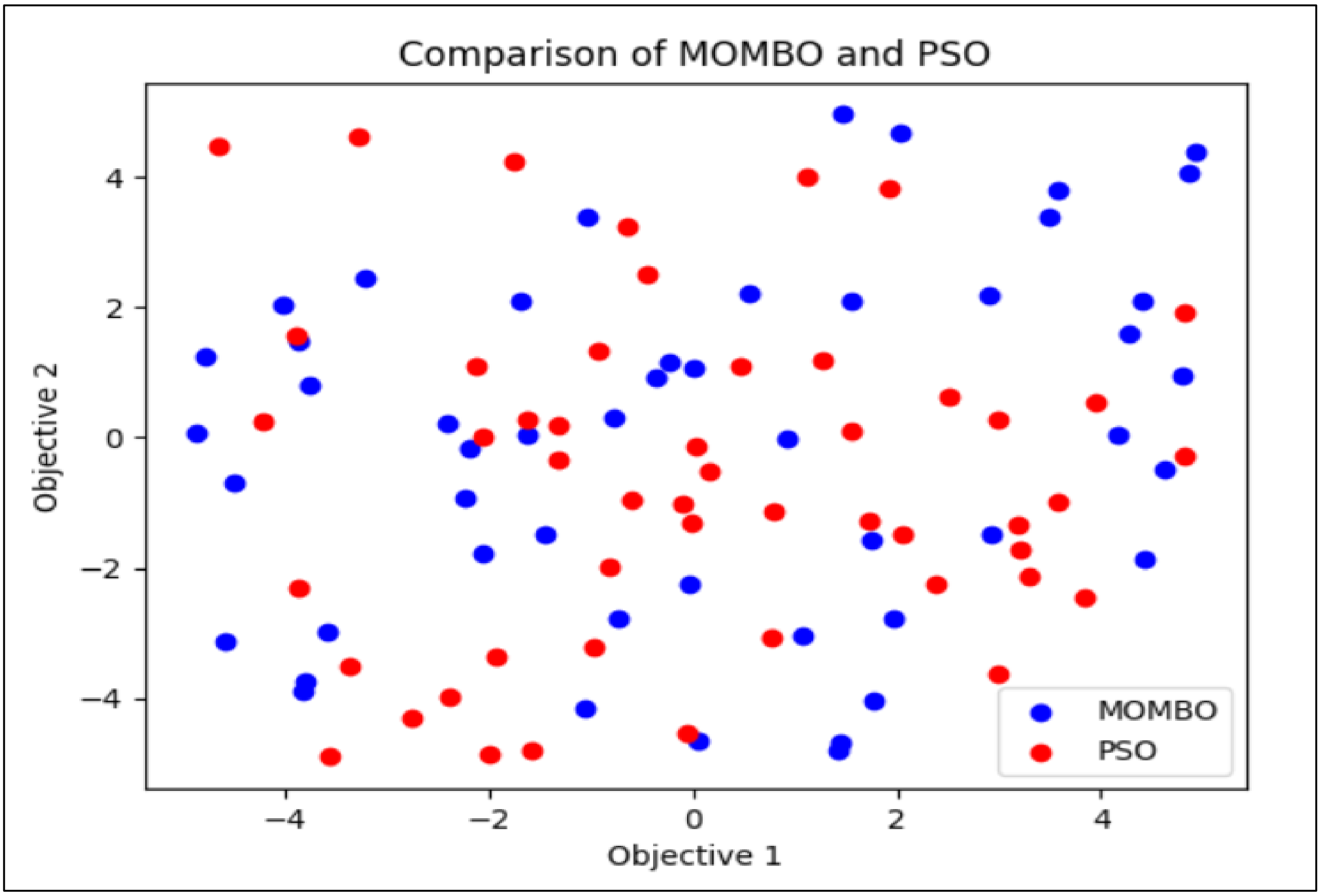

Fig 1: Comparison of MOMBO and PSO