# BINARY OPTIMIZER BASED ON HYBRIDIZATION OF PSO AND GWO

## Minor Project II


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# DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and beliefs, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma from a university or other institute of higher learning, except where due acknowledgment has been made in the text.

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# <u>CERTIFICATE</u>

This is to certify that the work titled "**BINARY OPTIMIZER BASED ON HYBRIDIZATION OF PSO AND GWO**" submitted by Manan Agarwal, Ayush Khandelwal, Abhinav Verma of B.Tech of Jaypee Institute of Information Technology, Noida has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of any other degree or diploma.

Digital Signature of Supervisor
Name of Supervisor
Designation
Date

# ABSTRACT

In this project, we have implemented the hybrid of Particle Swarm Optimization and Grey Wolf Optimization and then proposed and implemented the binary version of the hybrid.

The original PSOGWO is a hybrid optimization algorithm that benefits from the exploration ability of PSO and the exploitation ability of GWO. Even though the original hybrid approach gives better performance, it is appropriate only for problems with a continuous search space. However, feature selection is a binary problem and therefore, a binary version of the hybrid is proposed and implemented.

We have used 9 standard benchmark functions to evaluate the performance of this binary HPSOGWO. The results show that BHPSOGWO is significantly better than the original binary of GWO and PSO. The BHPSOGWO improved the global optimum value in some of the functions, while in all the others, it reached the global optimum value in fewer iterations than the original BPSO and BGWO.

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# Nomenclature

## English Symbols

$c1$ is the tendency of a particle to favour the personal minimum

$c2$ is the tendency of a particle to favour it's global minimum

$\chi$ is the constriction factor, corresponding loosely to the tendency of a particle to resist changing direction

g*Best* global best

*pBest* personal best

$Xp$ position of prey

$A$ coefficient vector

$X$ position of grey wolf

$a$ encircling coefficient

$X\alpha$ position of alpha wolf

$X_\beta$ position of beta wolf

$X_\delta$ position of delta wolf

$w$ inertia constant

# Abbreviations

| | |
|---|---|
| PSO | Particle swarm optimization |
| GWO | Grey Wolf optimizer |
| HPSOGWO | Hybrid of Particle swarm optimization and Grey Wolf Optimizer |
| BPSO | Binary Particle swarm optimization |
| BGWO | Binary Grey Wolf Optimizer |
| BHPSOGWO | Binary Hybrid of Particle swarm optimization and Grey Wolf Optimizer |
| GA | Genetic Algorithm |
| GSA | Gravitation Search Algorithm |
| DE | Combined Charging System |
| BFOA | Bacterial Foraging Optimization Algorithm |
| BSO | Bacterial Swarm Optimization |
| mGWO | modified Grey Wolf Optimizer |
| MGWO | Mean Grey Wolf Optimizer |
| SCA | Sine Cosine Algorithm |
| HGWOSCA | Hybrid of Grey Wolf Optimizer and Sine Cosine Algorithm |

# INTRODUCTION

In the early of 1990s, several studies regarding the social behaviour of animal groups were developed. These studies showed that some animals belonging to a certain group are able to share information among their group, and such capability confers these animals a great survival advantage.

Inspired by these works, **Kennedy** and **Eberhart** proposed **Particle Swarm Optimization** in 1995. As mentioned in the original paper, sociobiologists believe a school of fish or a flock of birds that moves in a group "**can profit from the experience of all other members**". In other words, while a bird flying and searching randomly for food, for instance, all birds in the flock can share their discovery and help the entire flock get the best hunt. PSO is a metaheuristic algorithm that is appropriate to optimize nonlinear continuous functions. The authors derived the algorithm inspired by the concept of swarm intelligence, often seen in animal groups, such as flocks and shoals.

**Grey wolf optimizer** (GWO) is a metaheuristic optimization method developed by **Mirjalili** and his colleagues in 2014. Normally, grey wolves live in a pack with a group size of 5 to 12. GWO mimics the hunting and searching prey characteristic of grey wolves in nature. In GWO, the population are divided into alpha, beta, delta, and omega. Alpha wolf is the main leader which is responsible for decision-making. Beta wolf is the second leader that assists the alpha in making the decision or other activities. Delta wolf is defined as the third leader in the group, which dominates the omega wolves. Searching for prey, encircling prey, and attacking prey are the three main steps of hunting, which are implemented to perform optimization.

Exploring the space of the search and exploiting the optimal solutions found are two contradictory principles to be considered when using or modelling a metaheuristic. Balancing exploration and exploitation in a good manner will led to the improvement of the search algorithm's performance. In order to achieve a good balance, one option is to utilize a hybrid approach where two algorithms or more are combined to improve each algorithm's performance and the resulted hybrid approach is named a memetic method.

**HPSOGWO** was presented with the combination of Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) by **Narinder Singh and S. B. Singh**. The main idea was to improve the ability of exploitation in Particle Swarm Optimization with the ability of exploration in Grey Wolf Optimizer to produce both variants' strength. The numerical and statistical solutions in their research paper show that the hybrid variant outperforms significantly the PSO and GWO variants in terms of solution quality, solution stability, convergence speed, and ability to find the global optimum.

A binary version of the hybrid grey wolf optimization and particle swarm optimization, BHPSOGWO is used to solve feature selection problems. The original version of the particle swarm has been operated in continuous space. But many optimization problems are set in discrete space. For this reason, the work carried out by Kennedy and Eberhart, in 1997 a reworking of the algorithm to operate on discrete binary variables. In spite of continuous PSO that trajectories are defined as changes in position on some number of dimensions, in the binary version of PSO, trajectories are changes in the probability that a coordinate will take on a zero or one value. Since 1995, PSO and BPSO are being researched and utilized in different subjects such as power systems, FPGA routing, TSP modelling, neural network learning, data clustering, feature selection, and other applications, by researches around the world.

## BACKGROUND STUDY

**Table: 1.1**

| | | |
|---|---|---|
| 1. | A. Ahmed, A. Esmin, and S. Matwin, "HPSOM: a hybrid particle swarm optimization algorithm with genetic mutation" | The main idea of the HPSOM was to integrate the Particle Swarm Optimization (PSO) with Genetic Algorithm (GA) mutation technique. The hybrid variant was significantly better than the Particle Swarm Optimization in terms of solution quality, solution stability, convergence speed, and ability to find the global optimum. |
| 2. | S. Mirjalili and S. Z. M. Hashim, "A new hybrid PSOGSA algorithm for function optimization" | The main idea is to integrate the capability of exploitation in Particle Swarm Optimization with the capability of exploration in Gravitation Search Algorithm to synthesize both variants' strength. The hybrid variant has been shown to possess a better capability to escape from local optimums with faster convergence than the PSO and GSA. |
| 3. | A. Ouyang, Y. Zhou, and Q. Luo, "Hybrid particle swarm optimization algorithm for solving systems of nonlinear equations" | Presented a hybrid PSO variant, which combines the advantages of PSO and Nelder-Mead Simplex Method (SM) variant, is put forward to solve systems of non-linear equations, and can be used to overcome the difficulty in selecting good initial guess for SM and inaccuracy of PSO due to being easily trapped into local optimum. |
| 4. | S. Yu, Z. Wu, H. Wang, Z. Chen, and H. Zhong, "A hybrid particle swarm optimization algorithm based on space transformation search and a modified velocity model" | Proposed a newly hybrid Particle Swarm Optimization variant to solve several problems by combining modified velocity model and space transformation search. The hybrid PSO holds good performance in solving both multimodal and unimodal problems. |
| 5. | X. Yu, J. Cao, H. Shan, L. Zhu, and J. Guo, "An adaptive hybrid algorithm based on particle swarm optimization and differential evolution for global optimization" | Proposed a novel algorithm, HPSO-DE, by developing a balanced parameter between PSO and DE. The newly hybrid variant finds better quality solutions more frequently, is more effective in obtaining better quality solutions, and works in a more effective way. |

| | | |
|---|---|---|
| 6. | S. M. Abd-Elazim and E. S. Ali, "A hybrid particles swarm optimization and bacterial foraging for power system stability enhancement" | Presented a newly hybrid variant combined with bacterial foraging optimization algorithm (BFOA) and PSO, namely, bacterial swarm optimization (BSO). In this hybrid variant, the search directions of tumble behaviour for each bacterium are oriented by the global best location and the individual's best location of Particle Swarm Optimization. |
| 7. | N. Mittal, U. Singh, and B. S. Sohi, "Modified grey wolf optimizer for global engineering optimization | Developed a modified variant of the GWO called modified Grey Wolf Optimizer (mGWO). An exponential decay function is used to improve the exploitation and exploration in the search space over the course of generations. |
| 8. | S. Singh and S. B. Singh, "Mean grey wolf optimizer" | Present a newly modified approach of GWO called Mean Grey Wolf Optimizer (MGWO). This approach has been originated by modifying the position update (encircling behaviour) equations of GWO. |
| 9. | N. Singh and S. B. Singh, "A novel hybrid GWO-SCA approach for standard and real" | Present a new hybrid swarm intelligence heuristic called HGWOSCA, a combination of Grey Wolf Optimizer (GWO) used for exploitation phase and Sine Cosine Algorithm (SCA) for exploration phase in uncertain environment. |
| 10. | J. Kennedy and R. Eberhart, "Particle swarm optimization" | Inspired by the simulation of the social behaviour of animals such as bird flocking and fish schooling. This approach is learned from animal's behaviour to calculate global optimization functions/problems and every partner of the swarm/crowd is called a particle. |
| 11. | S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer" | Inspired by the grey wolves and investigate its abilities in solving standard and real-life applications. The GWO variant mimics the hunting mechanism and leadership hierarchy of grey wolves in nature. |
| 12. | Narinder Singh, S. B. Singh, "Hybrid Algorithm of Particle Swarm Optimization and Grey Wolf Optimizer for Improving Convergence Performance" | Presented with the combination of Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). The main idea is to use the ability of exploration in Particle Swarm Optimization with the ability of exploitation in Grey Wolf Optimizer to produce both variants' strength. |

# REQUIREMENT ANALYSIS

System requirements for Python Installation:

- Operating system: Linux- Ubuntu 16.04 to 17.10, or Windows 7 to 11, with 2GB RAM (4GB preferable).
- Python 3.6 or above.
- Install NumPy, Matplotlib:
    1. Open the command prompt window
    2. Type in the following commands followed by the Enter key:
        a. python -m pip install numpy
        b. python -m pip install matplotlib

- Text Editor like VS Code, Sublime or any Python IDE.

# DETAILED DESIGN

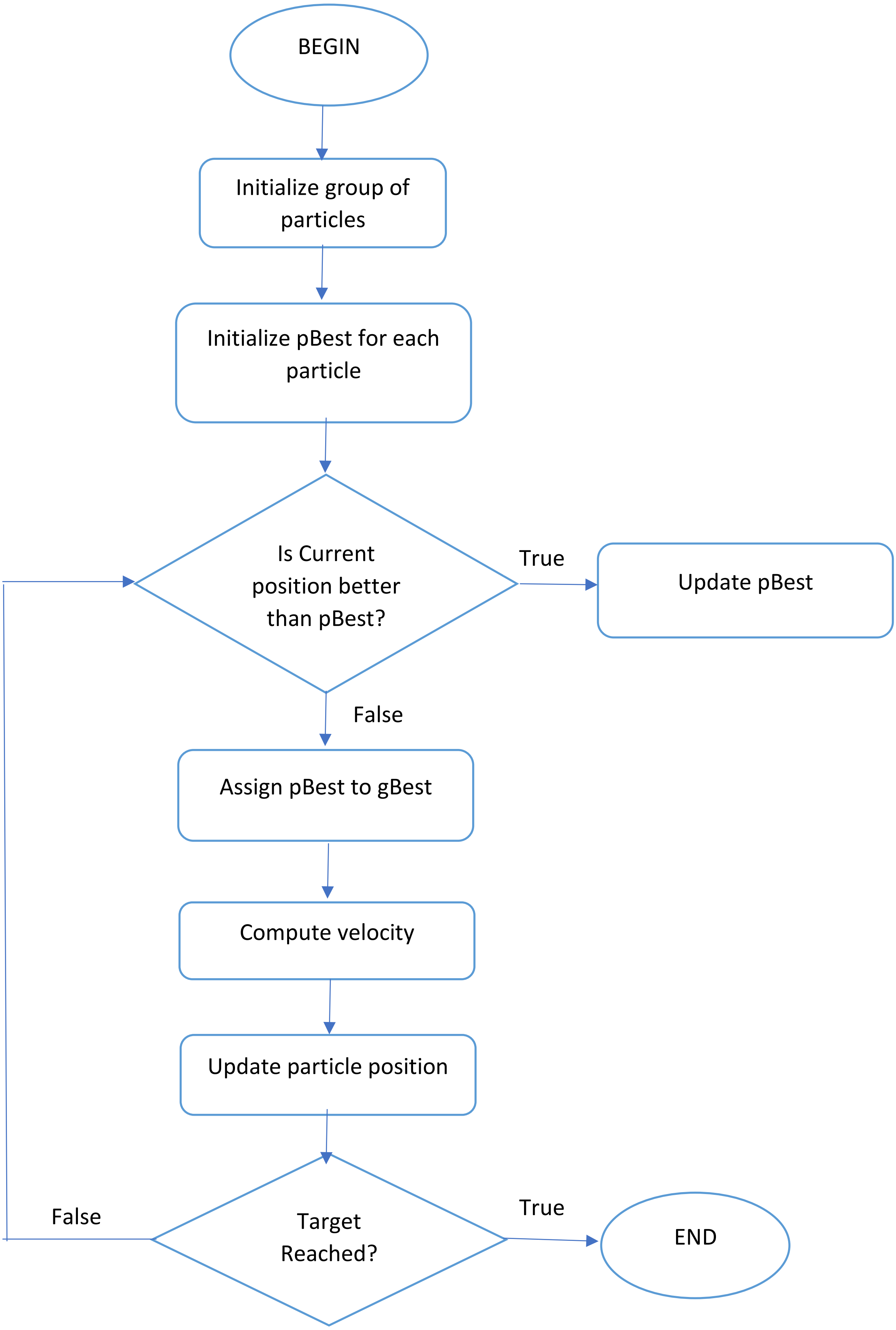


Fig.1.1 Flow chart of the Particle Swarm Optimization

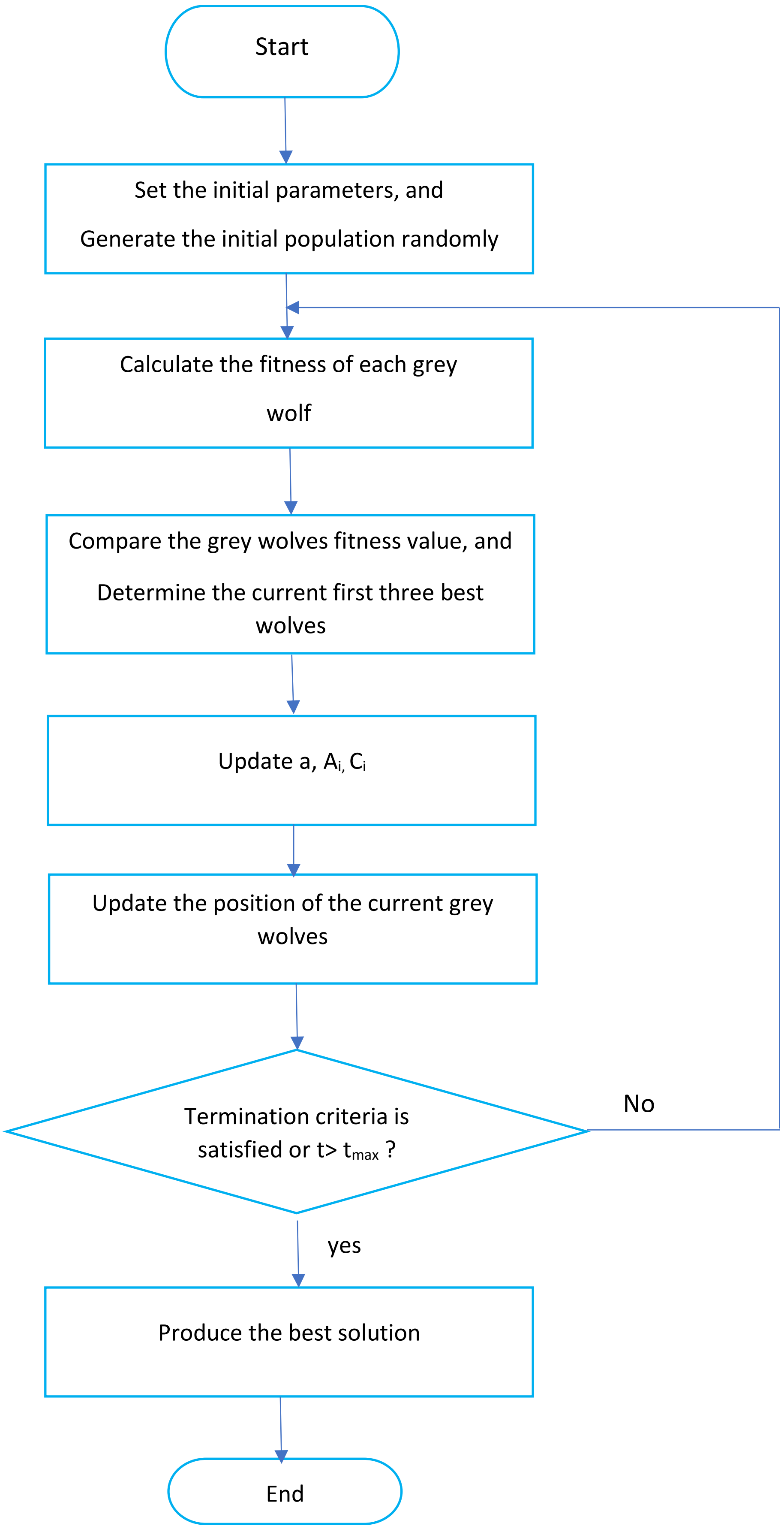


Fig.1.2 Flow chart of the Grey Wolf Optimizer

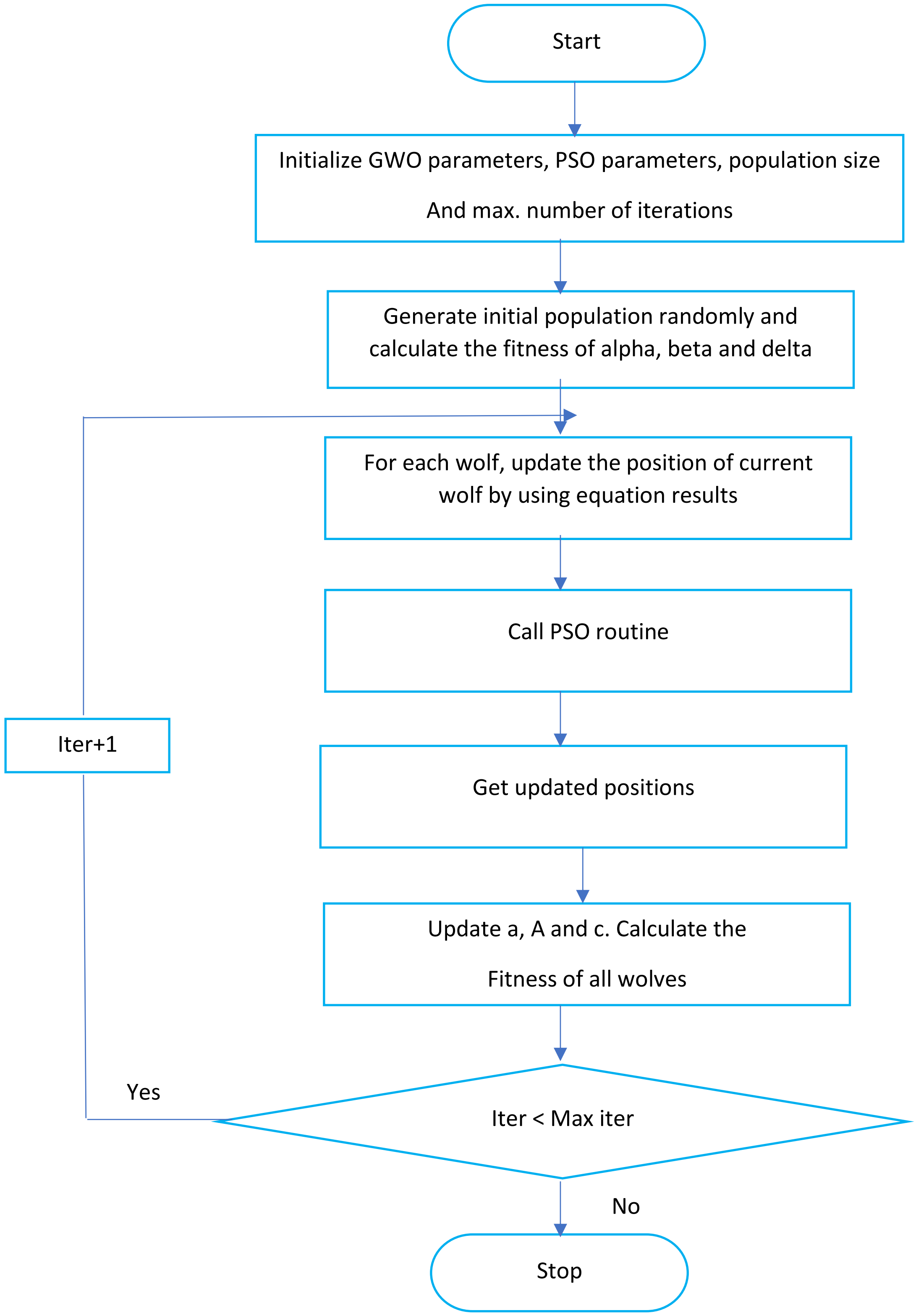


Fig.1.2 Flow chart of HPSOGWO

## IMPLEMENTATION

In Binary PSO, velocities of the particles are defined in terms of probabilities that a bit will change to one. Using this definition, a velocity must be restricted within the range [0,1].
The new position of the particle is obtained using the equation below:

$$x(t+1) = \begin{cases} 1, & r < S(v(t+1)) \\ 0, & otherwise \end{cases}$$

Where r is a uniform random number in the range [0,1]

In Binary GWO, update the position of wolf by converting the position into a binary vector

$$x(t+1) = \begin{cases} 1, & r \leq S((x1 + x2 + x3)/3) \\ 0, & otherwise \end{cases}$$

where,

$$S(x) = \frac{1}{1 + e^{-10(x-0.5))}}$$

In BHPSOGWO, the exploration and exploitation are controlled by an inertia constant weight

$$\vec{D}_{\alpha} = |\, \vec{C}_1 . \vec{X}_{\alpha} - w * \vec{X} \,|$$

$$\vec{D}_{\beta} = |\, \vec{C}_2 . \vec{X}_{\beta} - w * \vec{X} \,|$$

$$\vec{D}_{\delta} = |\, \vec{C}_3 . \vec{X}_{\delta} - w * \vec{X} \,| \qquad \text{Eq} - (1)$$

the velocity and positions have been updated as follows

$$v_i^{k+1} = w * [v_i^k + c_1 r_1 \left(x_1 - x_i^k\right) + c_2 r_2 \left(x_2 - x_i^k\right) + c_3 r_3 \left(x_3 - x_i^k\right)] \qquad \text{Eq} - (2)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad \text{Eq} - (3)$$

## Pseudocode for **BHPSOGWO**

Initialization
Initialize *A, a, c* and w

Randomly Initialize an agent of n wolves' positions ∈ [1,0]

Based on the fitness function attain the α, β, δ solutions

Evaluate the fitness of agents by using Eq – (1)
While (t < Max_iter)
    For each population

        Update the velocity using Eq – (2)

        Update the position of agents into a binary position based on above equation Eq – (3)

    end

    Update *A, a, c and w*
    Evaluate all particles using the objective function
    Update the positions of the three best agents α, β, δ;

    t = t+ 1

end while
The solution in this study is illustrated in a one-dimensional vector. The length of this vector is equal to the number of features. In this binary vector, 0 and 1 have the following meaning:

- 0: feature is not selected
- 1: feature is selected

## Benchmark Functions:

| S.No. | Function name | Test Function |
|---|---|---|
| 1 | Sphere model (F1) | $f_1(x) = \sum_{i=1}^{n} (x_i)^2$ |
| 2 | Schwefel's problem 2.22 (F2) | $f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$ |

| | | |
|---|---|---|
| 3 | Generalized Rastrigin's Function (F3) | $$f_3(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$$ |
| 4 | Schwefel's problem 2.21 (F4) | $$f_4(x) = \max\{\lvert x_i\rvert, 1 \le i \le n\}$$ |
| 5 | Generalized Rosenbrock' s Function (F5) | $$f_5(x) = \sum_{i=1}^{n-1}[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2]$$ |
| 6 | Step Function (F6) | $$f_6(x) = \sum_{i=1}^{n}([x_i + 0.5])^2$$ |
| 7 | Ackley's Function (F7) | $$f_7(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e$$ |
| 8 | F8 | $$f_8(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$ |
| 9 | F9 | $$f_9(x) = \left\{\sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \left(\sum_{i=1}^{n} u(x_i, 5, 100, 4)\right)$$ |

# EXPERIMENTAL RESULTS AND ANALYSIS

Sphere model (F1)

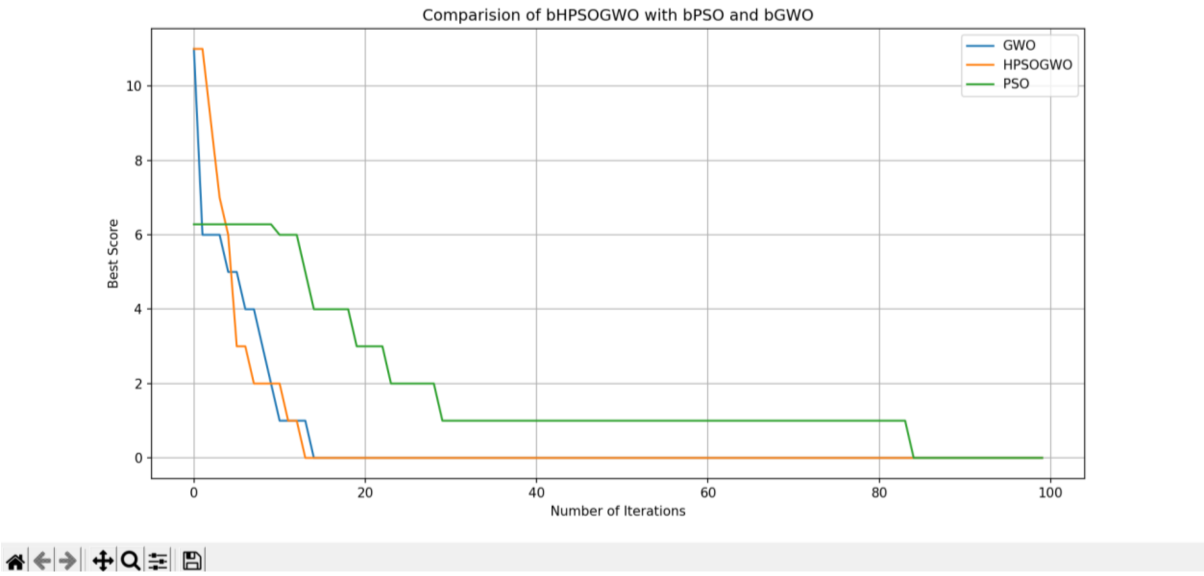


Fig. 1.4

Schwefel's problem 2.22 (F2)

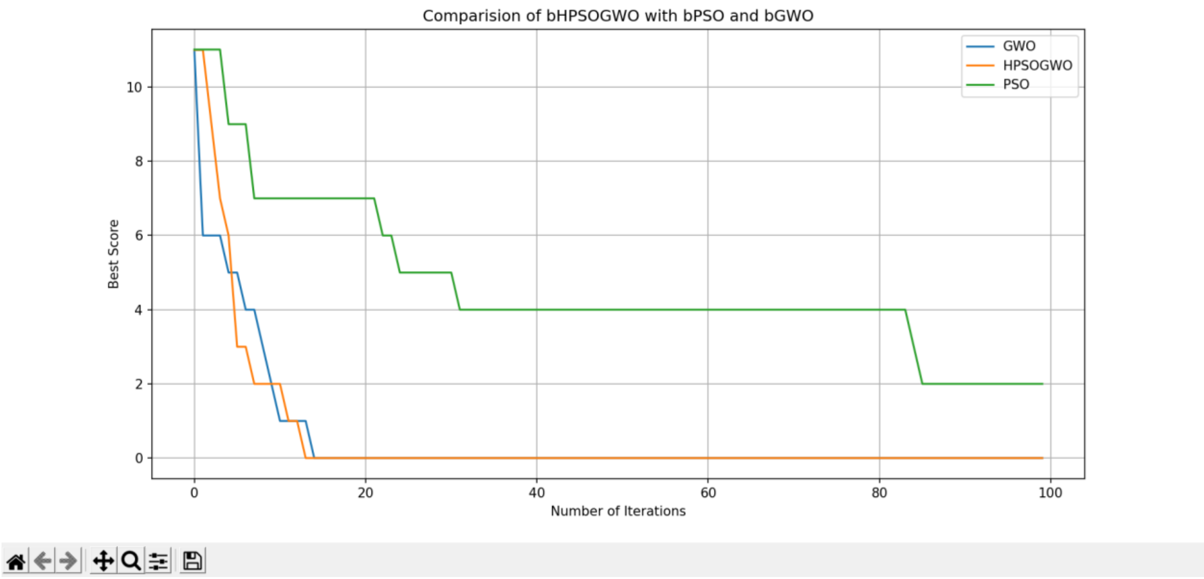


Fig. 1.5

Generalized Rastrigin's Function (F3)

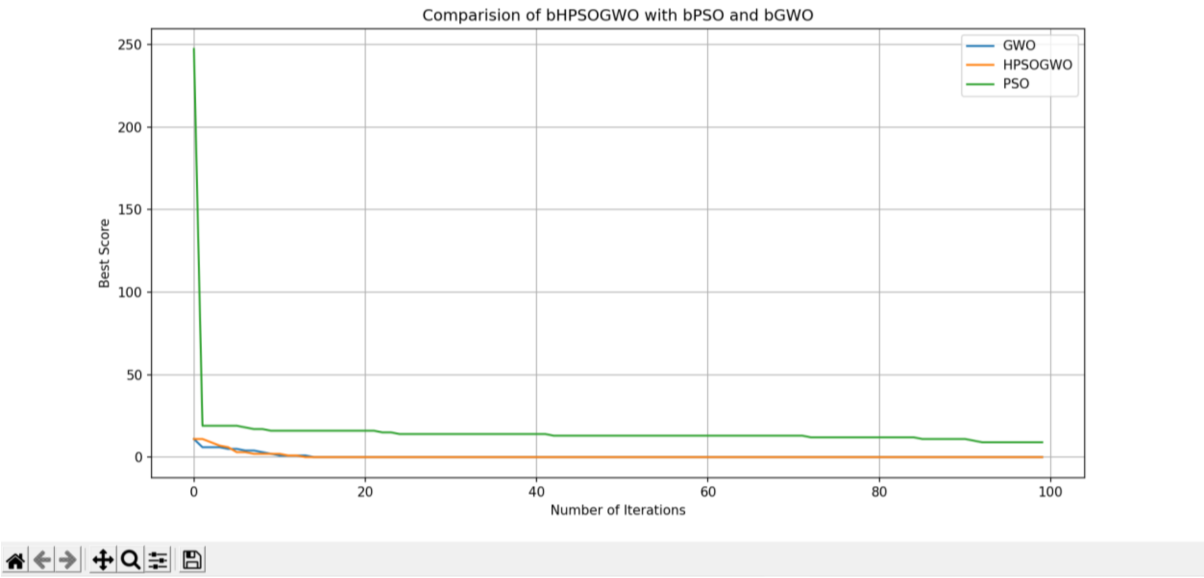


Fig. 1.6

Schwefel's problem 2.21 (F4)

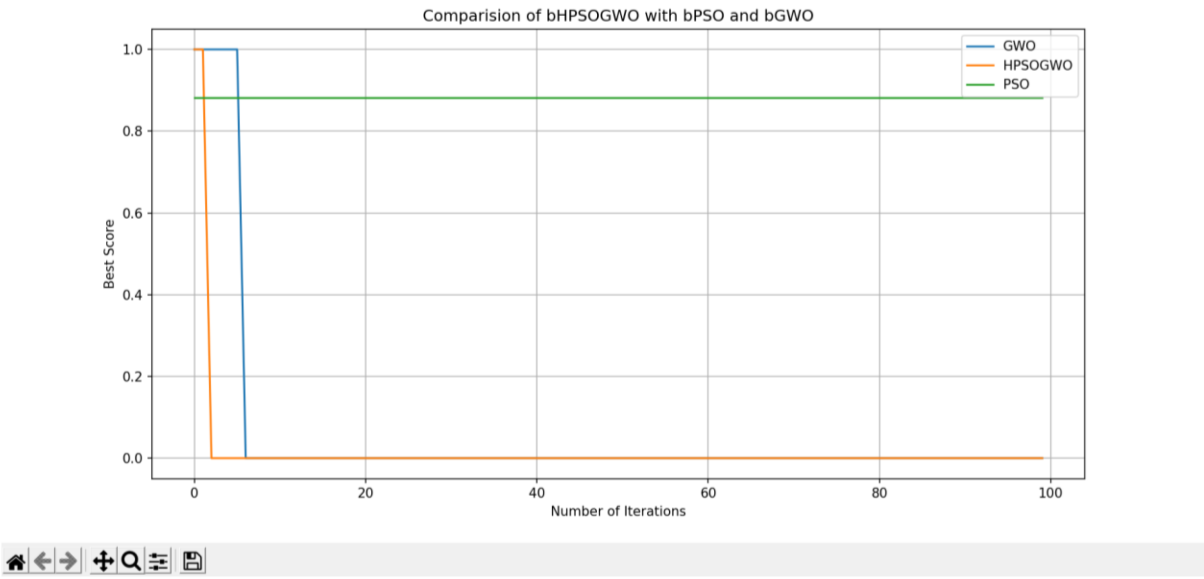


Fig. 1.7

Generalized Rosenbrock' s Function (F5)

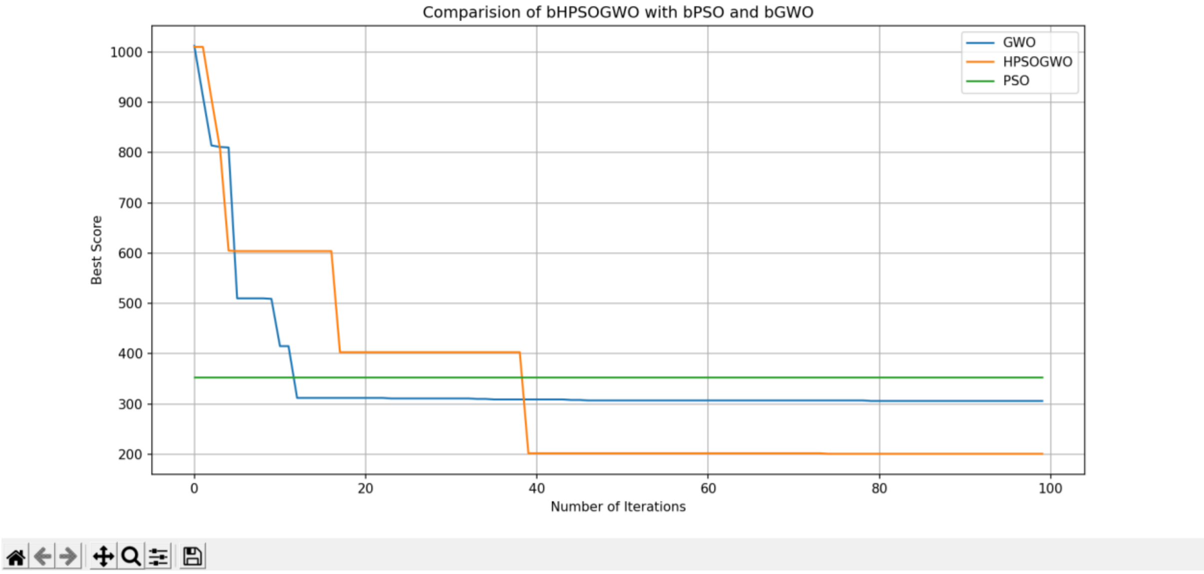


Fig. 1.8

Step Function (F6)

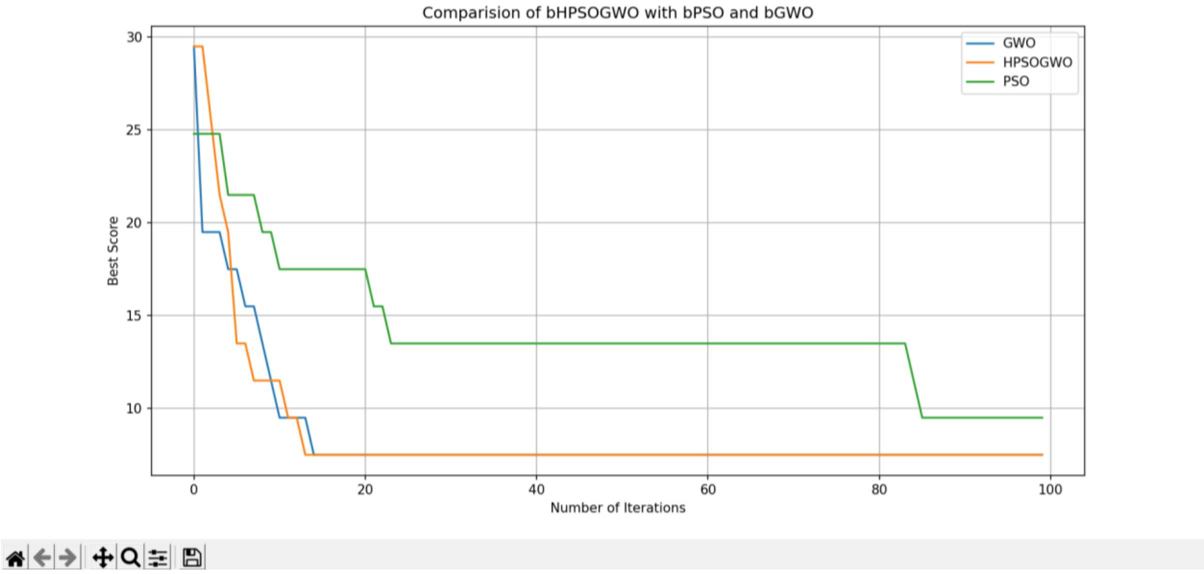


Fig. 1.9

Ackley's Function (F7)

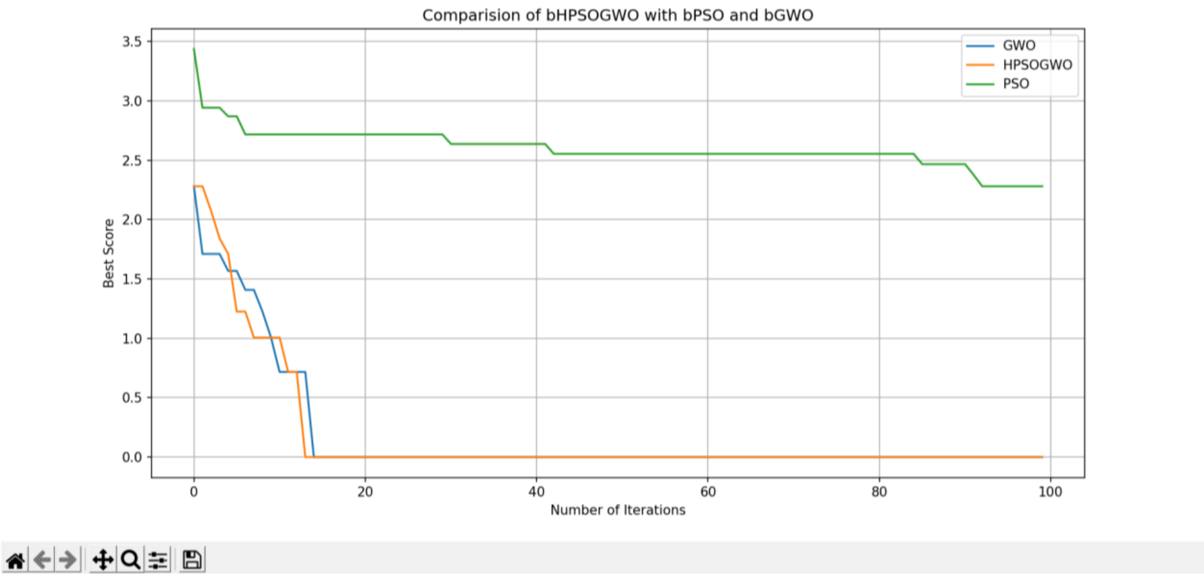


Fig. 1.10

F8

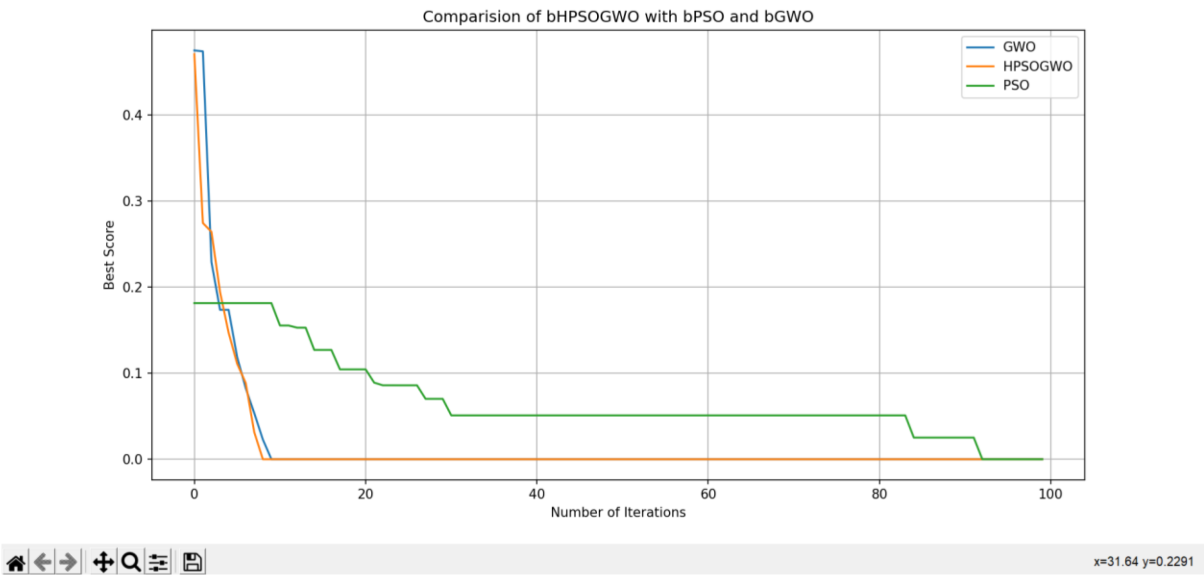


Fig. 1.11

F9

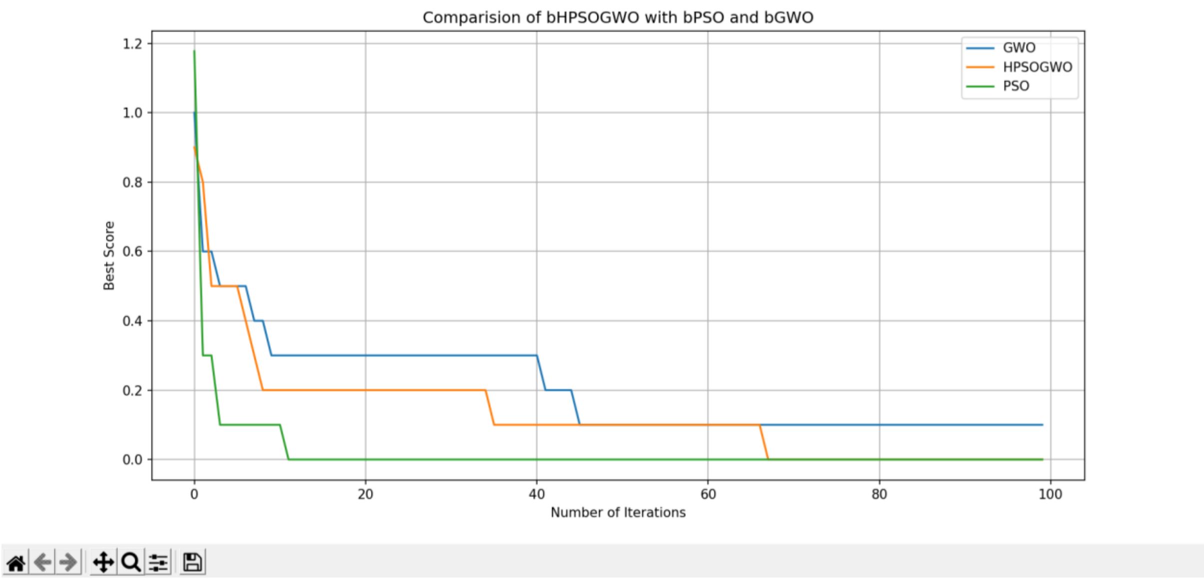


Fig. 1.12

**Table 1.2: Comparison using Benchmark functions**

| Function name | bPSO (iter, min_value) | bGWO (iter, min_value) | bHPSOGWO (iter, min_value) |
|---|---|---|---|
| Sphere model | 85, 0 | 15, 0 | 14, 0 |
| Schwefel's problem 2.22 | 86, 2 | 15, 0 | 14, 0 |
| Generalized Rastrigin's Function | 93, 9 | 15, 0 | 14, 0 |
| Schwefel's problem 2.21 | 1, 0.8819 | 7, 0 | 3, 0 |
| Generalized Rosenbrock' s Function | 1, 353.3652 | 80, 306.0 | 75, 201.0 |
| Step Function | 86, 9.5 | 15, 7.5 | 14, 7.5 |
| Ackley's Function | 93, 2.28119 | 15, 4.4408e-16 | 14, 4.44089e-16 |
| F8 | 93, 0 | 10, 0 | 9, 0 |
| F9 | 12, 1.3497e-32 | 46, 0.1 | 68, 1.3497e-32 |

## Analysis:

From the above Table (Table 1.2) and Figures (Fig 1.4-1.11), we analysed that Binary of HPSOGWO outclassed the other two algorithms namely, Binary PSO and Binary GWO. BHPSOGWO reaches a better minimum value than both bPSO and bGWO in some cases (like Generalized Rosenbrock' s Function) and was able to give that value in fewer iterations than bPSO and bGWO in all the cases.

Thus, it can be said from above results that we can solve binary optimisation problems with greater efficiency and effectiveness by Hybridising two algorithms.

In 1 of the 9 test functions, PSO reached the optimal value first. In the remaining benchmark functions, the Binary Hybrid achieved the optimal value first, which shows an efficiency of 88.88%. In 66.66% of the test cases the Binary PSO got stuck at the local optimum.

# CONCLUSION OF THE REPORT AND FUTURE SCOPE

In this project, the binary version of HPSOGWO was proposed, implemented, and is used to solve the problem of feature selection, which is a binary problem. To check the efficiency and effectiveness of BHPSOGWO we used 9 standard benchmark functions. This proposed hybrid model was compared with two algorithms namely BPSO and BGWO. The results showed the excellence of this proposed algorithm when compared with other two algorithms. This hybrid model benefits from various parameters over the other two such as smaller number of iterations, lesser execution time and reaching a more optimal value.

As far as this hybrid model is concerned there are various scope of future works. We would recommend employing this algorithm to solve another real-world problem such as engineering optimization problems, scheduling problems and/or molecular potential energy function. Furthermore, this proposed method can be experimented with other classifiers such as Artificial Neural Network (ANN) and Support Vector Machine (SVM) which are tough competitor of K-Nearest Neighbour algorithm (KNN) to evaluate whether performance is stable or varies. Another possible future work could be to hybridize the GWO or PSO with recent optimization techniques such as Salp Swarm Algorithm (SSA), Ant Lion Optimizer (ALO) and Dragon Algorithm (DA).

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