COMPARISON OF PARTICLE SWARM OPTIMIZATION AND GENETIC ALGORITHM

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Abstract: This paper focuses on comparison between the two very similar evolutionary algorithms : Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The paper starts with a brief introduction on these two algorithms for highlighting the computational procedures that each follows. Comparison is made using five CEC 2005 mathematical benchmark functions: F1(Shifted Sphere Function),F2(Shifted Schwefel's Problem),F6(Shifted Rosenbrock's Function), F7(Shifted Rotated Griewank's Function) and F9(Shifted Rastrigin's Function).

Introduction:

1. Particle Swarm Optimization (PSO) was invented by Kennedy and Eberhart[1] in the mid 1990s while attempting to simulate the choreographed navigation of flock of birds as part of a sociocognitive study investigating the paradigm of "collective or swarm intelligence" in the biological populations. PSO is now one of the most well-known algorithm in the literature of optimization and belongs to class of metaheuristics. One of key points in PSO is its simplicity.

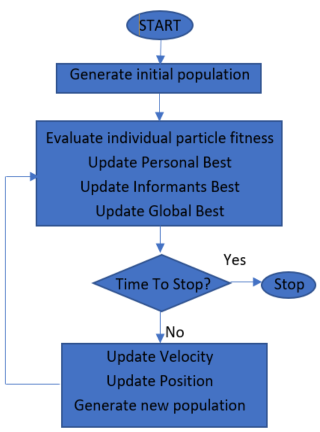


Figure 1.Flowchart for PSO

The new velocity is obtained as : $V_{i+1} \leftarrow \alpha V_i + \beta*rand()*(X_i^* - X_i) + \gamma *rand()*(X_i^+ - X_i) + \delta *rand()*(X_i^! - X_i)$ where V_i is the velocity of the particle, X_i is particles current position, X_i^* is the particles best position so far, X_i^+ is informants best position so far and $X_i^!$ is the global best position of any particle. α, β, γ, δ is the weight corresponding to each components. The new position is updated as : $X_{i+1} \leftarrow X_i + \varepsilon V_{i+1}$.

Following are the results obtained in PSO by varying different hyperparameters like α, β, γ, δ for the all the multimodal (F6,F7,F9)and unimodal (F1,F2) functions used.

Settings	Convergence State
α=0.9,β=1.5,γ=0,δ=0	No convergence
α=0.7,β=1.5,γ=0,δ=1.5	Trapped in local optimum
α=0.7,β=1.5,γ=1.5,δ=0	Stagnate
α=0.7,β=1.5,γ=1.5,δ=5	Stagnate
α=0.7,β=5,γ=1.5,δ=1.5	Converging very slowly
α=0.7,β=1.5,γ=5,δ=1.5	Stagnate
α=0.7,β=1.5,γ=1.5,δ=1.5	Good performance on unimodal functions
α=0.7,β=2,γ=2,δ=2	Good performance on multimodal functions.

When we are keeping the social component δ and the informant component γ as minimum ,then there is no exchange of information between particles and they thus fail to converge to the global optimum. Weighting these components too much cause the population progress to stagnate . When we keep the value of α as 0.7 , it improved the model performance. Number of informants are selected as 4 ,since 4 was giving good performance when tried with different CEC benchmark functions using number of informants from 1 to 10.

2 .Genetic Algorithm(GA) is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation[3].There are many versions of GA. In this study a population of fixed-length vectors of real numbers with tournament selection ,two point crossover and uniform random mutation are employed to optimize the selected five benchmark problems.

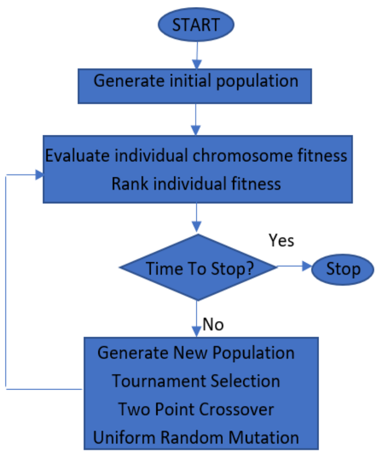


Figure 2.Flowchart for GA

Following table shows the observations obtained when increasing the number of genes D in a chromosome.

Dimension	**Convergence**
10	Slow
20	Fast

As we increase the dimension of chromosome ,the performance of GA is also increasing.

Choosing CEC Benchmark Functions:

The five CEC Benchmark functions that I had took for comparing performance of PSO and GA are: F1(Shifted Sphere Function),F2(Shifted Schwefel's Problem),F6(Shifted Rosenbrock's Function), F7(Shifted Rotated Griewank's Function) and F9(Shifted Rastrigin's Function). F1 and F2 are unimodal functions ,while F6 ,F7and F9 are multimodal non linear functions. I had chosen these functions because its implementation is easy and for comparing the behavior of PSO and GA in unimodal and multimodal function optimization.

Comparison Between GA and PSO:

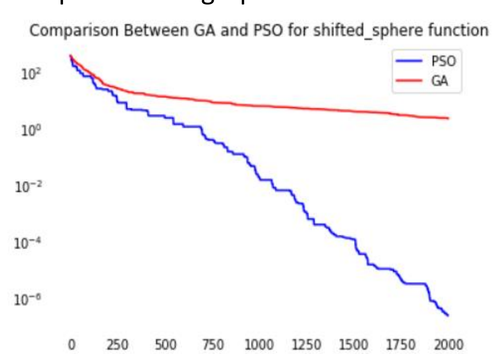
This section will compare the performance of standard PSO and GA on the above mentioned five benchmark functions.

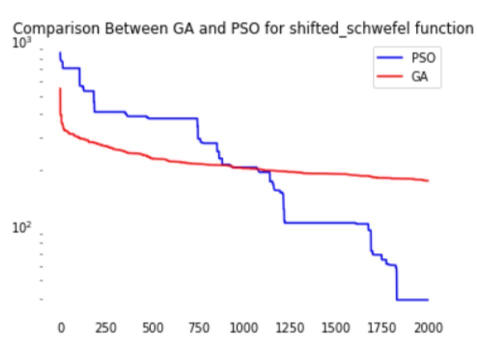
a. Both PSO and GA is having 20 particles or chromosomes with dimension as 20.
b. Number of iterations/generations=2000

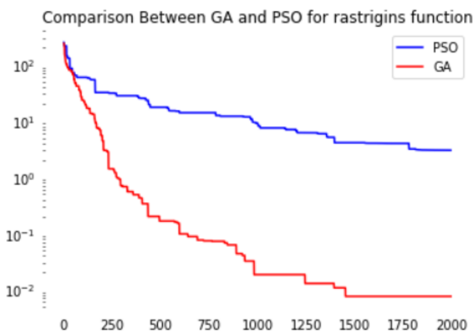
Following table shows the numerical results of comparison between PSO and GA. For all functions both algorithms had ran 5 times and the mean value is given in the table.

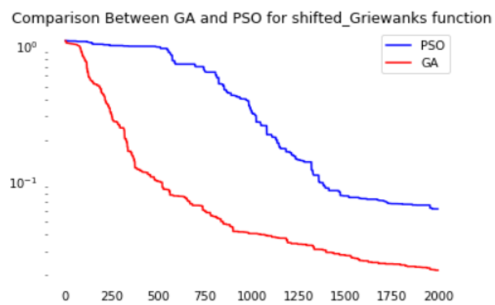
Functions	**PSO**	**GA**
Shifted Sphere	3.67x10^{-5}	3.24
Shifted Schwefel's	30.23	145.2
Shifted Rosenbrock's	20.076	154.01
Shifted Rotated Griewank's	0.860	0.041
Shifted Rastrigin's	6.96	.0162

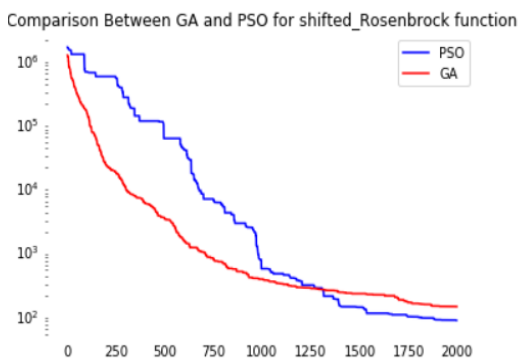
The optimization graph obtained is as following:







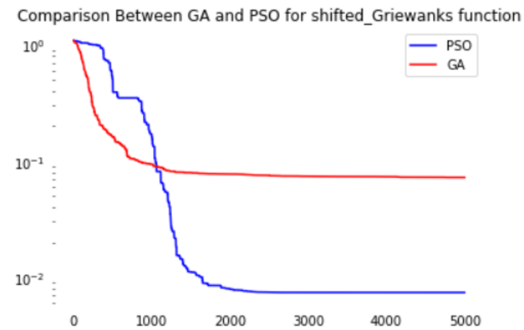


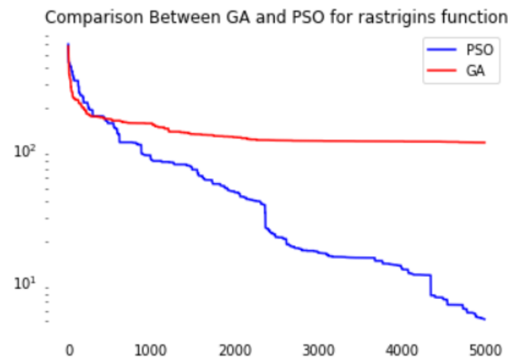


Let us now try these functions with number of iterations/generations=5000.Following table show the mean of the results obtained from running the algorithms five times for Shifted Rastrigins Function and Shifted Griewanks Function.

Functions	**PSO**	**GA**
Shifted Griewank's	0.0098	0.0459
Shifted Rastrigin's	6.214	53.09

Following graph shows results obtained with number of iterations=5000.





Conclusions:

The optimization algorithms that are inspired by the natural evolutions mostly performs good in most of the complex problems. At first in unimodal functions the standard PSO converges to the global optimum, but with the multimodal functions like Shifted Rastrigin's and Shifted Rotated Griewank's standard PSO gets trapped in the local optimum as discussed in reference[4]. In PSO, each particle is kept in confined space with limitations of corresponding parameters. This causes decrease in diversity of particles. If the global best particle does not change its position for some time, then it results in stagnation of search progress. This cause the PSO to not to be able to reach the global optimum[5]. But as we increase the number of iterations further we can see PSO is showing good performance than GA by trying to converge to the global optimum. PSO is also computationally cheaper when compared to GA.

References:

[1] Kennedy, J. and Eberhart, R., *"Particle Swarm Optimization," Proceedings of the IEEE International Conference on Neural Networks*, Perth, Australia 1995, pages 1942-1945.

[2] Jose M. Chaquet and Enrique J. Carmona "*A Grid-based Genetic Algorithm for Multimodal Real Function Optimization",* pages 158.

[3] Vijini Mallawaarachchi "*Introduction To Genetic Algorithms*"

[4] Varis Limlawan and Pisut Pongchairerks "*A PSO with ability to Avoid Being Trapped in a Local Optimum*"

[5] K. Premalatha and A.M.Natarajan "*Hybrid PSO and GA for Global Optimization*"

[6]http://web.mysites.ntu.edu.sg/epnsugan/PublicSite/Shared%20Documents/CEC2005/Tech-Report-May-30-05.pdf

[7]https://www.youtube.com/watch?v=JhgDMAm-imI

[8] https://www.youtube.com/watch?v=sB1n9a9yxJk

[9] https://nathanrooy.github.io/posts/2016-08-17/simple-particle-swarm-optimization-with-python/