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Meta- Heuristic based Optimization Algorithms: A Comparative Study of Genetic Algorithm and Particle Swarm Optimization

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Abstract: - The meta heuristic based optimization algorithms have been popular in the engineering mainly because of their tendency to efficiently solve multimodal, mixed integer nonlinear complex optimization problems. Genetic algorithm(GA) and particle Swarm optimization(PSO) are among the most popular meta heuristic methods. GA is inspired from the theories of evolutions and genetics while PSO mimics the collaborative behavior of swarm. GA and PSO are very much similar to each other because these two methods are evolutionary heuristic based search methods. This paper gives an overview of the GA and PSO and verifies and reinforces the claim that both GA and PSO have identical effectiveness but PSO has significantly better computational efficiency when compared to GA. This is done by performing the comparative study between GA and PSO using STYBLINSKI-TANG and MICHALEWICZ functions as the test functions.

Keywords: Meta-heuristic, Optimization, Genetic Algorithm, Particle Swarm Optimization, Fitness function.

I. INTRODUCTION

Meta-heuristic algorithms are high-level heuristics techniques designed to solve optimization problem that may yield a superior solution, even with incomplete or imperfect information [1]. Optimization can be defined as the process of minimization or maximization of the given objective function. Objective, fitness or evaluation function is the measure of improvement in the system. The meta-heuristic algorithms have edge over classical iterative methods because in these algorithms there is less chances of convergence to local optimum further they are more accurate and more efficient. The GA imitate the behavior of reproduction and evolution in biological populations. Usually GA gives an approximate solution to the given problem [3]. GA has been very effective in various problems such as numerical optimization, robotics, design, management and scheduling [4], power systems analysis [5], data exception and handling [3] etc.

Particle Swarm Optimization (PSO) was enunciated by Eberhart and Kennedy in 1990's. PSO work by assuming each particle as a potential solution which is refined and updated by the cognitive behavior gained through the particle own experience and the social behavior gained through the experience from the neighboring particles [6]. PSO has been used due to its several advantages over other meta-heuristic methods like robustness, efficiency and simplicity [7].

II. GENETIC ALGORITHM

In genetic algorithms(GA), initially a random population is generated that represents possible candidate solution to the given problem which evolves during optimization process towards better possible solutions. In each cycle, the fitness of every individual in it is evaluated with which multiple individuals are stochastically selected and modified to form a new generation. The newly generated population in each cycle is then used for the next iteration. The algorithm terminates either when one or both conditions are fulfilled i.e. the limit has been reached for maximum generations, or some user defined fitness level has been reached. In case algorithm termination due to maximum number of iterations, solution may or may not be satisfactory [8].
The various components of GA are discussed below:

A. Representation

Representation is the first design step which involve mapping of phenotype search space onto the genotype search space. Optimization takes place in genotype search space which can be very much different from phenotype space.

B. Fitness Function

The fitness function facilitates improvements in generation and establishes the selection criteria. This procedure develops a qualitative measure from the phenotype search space and associates that qualitative measure to genotypes.

C. Population

Population is the dynamic multiset of all possible solutions. The population is composed of static individuals and forms the basis of evolution.

D. Parent selection:

Parent selection or mating selection distinguishes individuals on the basis of their fitness value, and selects the individuals with higher fitness to become for matting of the next generation. In Evolutionary algorithms, matting selection approach is usually probabilistic.

E. Mutation and Recombination:

A mutation and recombination are unary and binary variation operators respectively. Application of mutation operator on any genotype results in a modified mutant called offspring or child. In general, mutation purpose is to create randomness and unbiased changes in data. Recombination operator combines attributes from two parents into offspring. In Genetic Algorithms, recombination operator is the main search operator. Both mutation and recombination operators are stochastic in nature.

F. Survivor selection

The survivor selection applies on already created offspring of the selected parents. The purpose of the survivor selection is to differentiate among individuals based on their fitness value. Survivor selection is often deterministic and also called replacement.

G. Initialization and Termination:

The initialization involves seeding a random population. The termination condition terminates the algorithm when either a desired solution is achieved or the required maximum generations are generated.

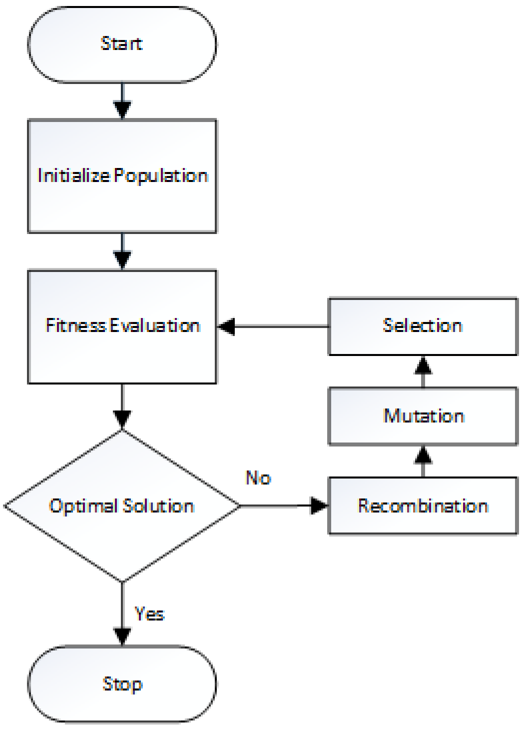

Fig. 1 Flow Chart of Genetic Algorithm.

III. PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) was initially designed to study the movement of birds when seeking food, referred as “cornfield vector” [9]. The birds are able to find food through social cooperation with each other in neighborhood. This idea was exploited in PSO for multidimensional search.

PSO is a metaheuristic based optimization algorithm that optimizes a problem by iteratively refining the candidate solution by comparing its fitness value. PSO is classified as the metaheuristics based optimization algorithm because it optimizes the problem without making any assumption about the given problem. PSO is capable of searching very large space of feasible solutions but can’t guarantee an optimal solution because of its metaheuristic nature.

The advantage of PSO over other classical optimization methods is that it does not optimizes a problem by using its gradient i.e. it can also optimize problems that are non-differentiable in nature. Therefore, PSO is also be used for problems that are highly irregular, noisy, varies with time etc. [10]

PSO works by initiating a population (called swarm) of candidate solutions (called particles). According to some well-defined PSO formulae these particles are moved in the search-space with the given considerations of their own known local best position along with the best known position entire swarm in the search-space [7]. These particles constantly try to discover improve positions which when discovered will direct the motion of the swarm. The process is continued until the achievement of a satisfactory solution.

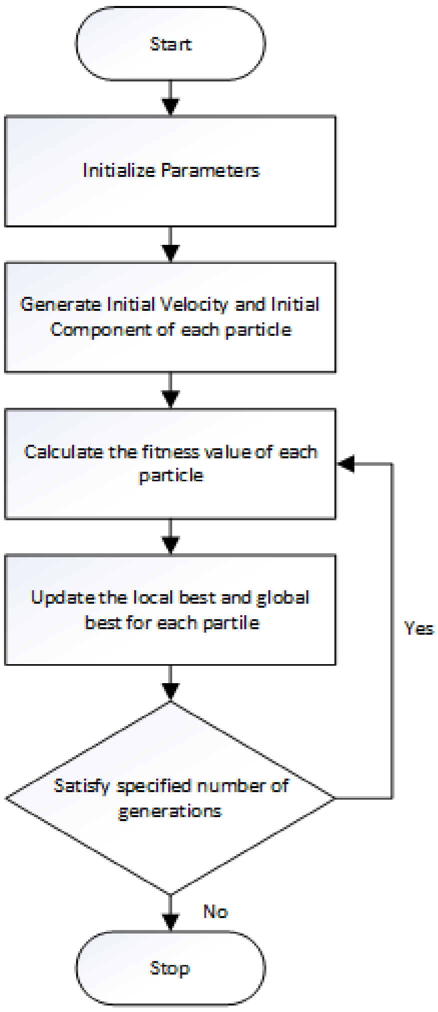

Fig. 2 Flow Chart of Particle Swarm Optimization.

IV. CASE STUDY

For case study STYBLINSKI-TANG function and MICHALEWICZ function are selected as test functions.

These functions are multidimensional functions usually used as evaluation functions for N dimensional optimization problems [11].

STYBLINSKI-TANG function is given below:

$$f(x) = \frac{1}{2}\sum_{i=1}^{N}(x_i^4 - 16x_i^2 + 5x_i) \quad (1)$$

The 2-D STYBLINSKI-TANG function is shown here in fig. 3:

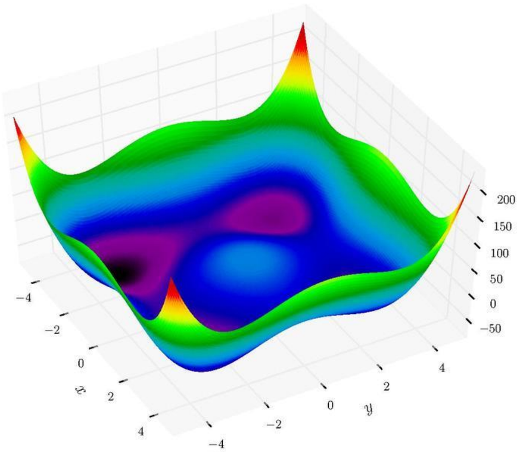

Fig. 3 2-Dimensional STYBLINSKI-TANG function

Function evaluation on the hypercube:

$x_i \in [-5, 5]$ for all i = 1,2,3 ..., N

Global minimum is at:

$$f(x^*) = -39.16599 \times N$$
$$x^* = (-2.903534, \dots\dots\dots, -2.903534)$$

Genetic algorithm and particle swarm optimization are evaluated using the given functions in search spaces. The evaluation results are plotted in MATLAB in terms of number of iterations and fitness value.

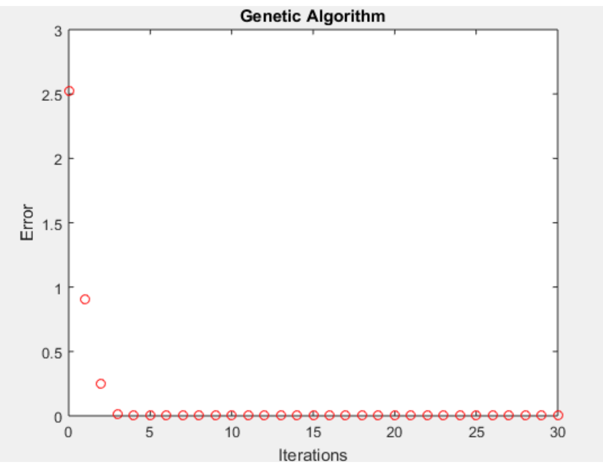

Fig. 4 Fitness vs Iteration Graph of 1-D STYBLINSKI-TANG function evaluated by GA

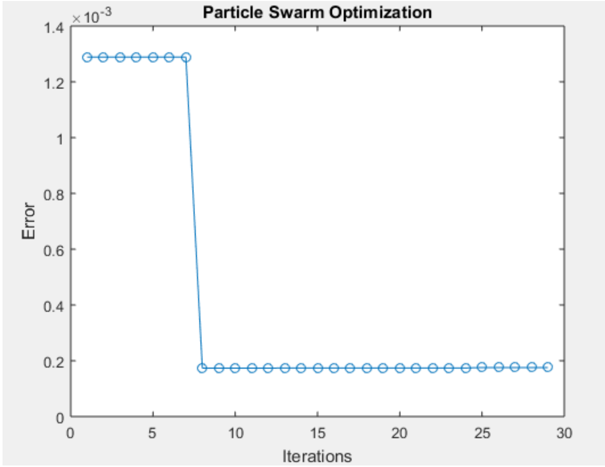

Fig. 5 Fitness vs Iteration Graph of 1-D STYBLINSKI-TANG function evaluated by PSO

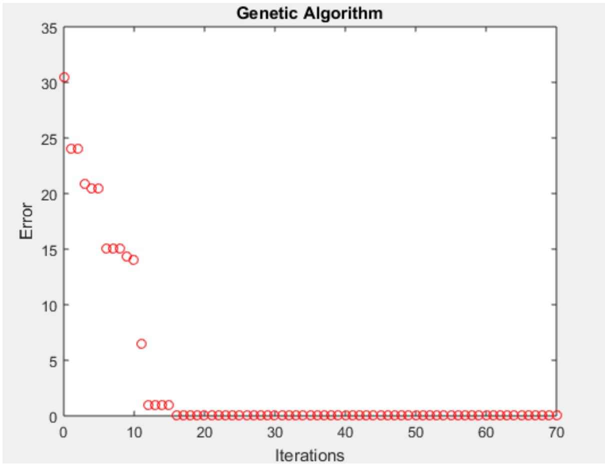

Fig. 6 Fitness vs Iteration Graph of 3-D STYBLINSKI-TANG function evaluated by GA

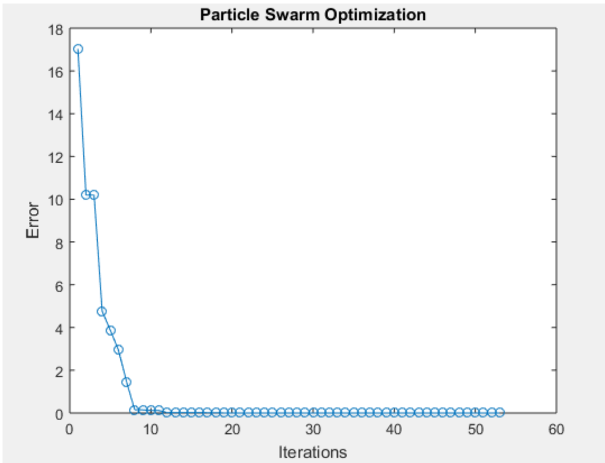

Fig. 7 Fitness vs Iteration Graph of 3-D STYBLINSKI-TANG function evaluated by GA

The 2-D MICHALEWICZ function is given below:

$$f(x) = -\sum_{i=1}^{N}\sin(x_i)\, sin^{2m}\left(\frac{i{x_i}^2}{\pi}\right) \quad (2)$$

The parameter ‘m’ defines the steepness of the valleys and ridges, a larger value of m causes more steepness in function, thus making search space more difficult [12]. The recommended value of ‘m’ is 10. The ‘N’ represents the dimension of search space of MICHALEWICZ function, for 2-D search space N=2.

The 2-D MICHALEWICZ function is shown in fig. 8:

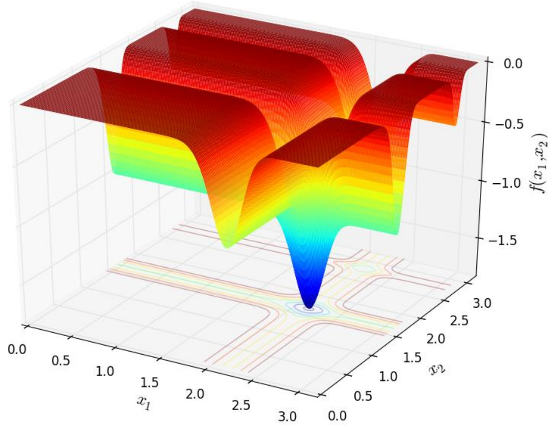

Fig. 8 2-Dimensional MICHALEWICZ function

Function evaluation on the hypercube:

$$x_i \in [0, \pi], \text{ for all } i = 1, \ldots, N.$$

Global minimum is at:

$$f(x^*) = -1.8013034101 \; at \; x^* = (2.20, 1.57)$$

Genetic algorithm and particle swarm optimization are further evaluated using 2-D MICHALEWICZ function The evaluation results are plotted in MATLAB in terms of number of iterations vs fitness value and are shown here in fig. 9-10

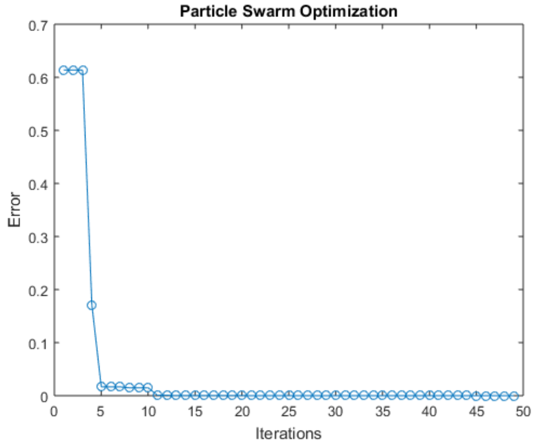

Fig. 9 Fitness vs Iteration Graph of 2-D MICHALEWICZ function evaluated by PSO

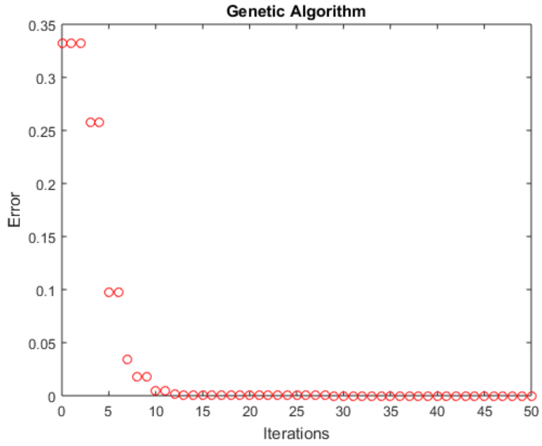

Fig. 10 Fitness vs Iteration Graph of 2-D MICHALEWICZ function evaluated by GA

From fig. 4-5 it is clear that number of iterations and fitness value for both methods are almost same for 1-D optimization but in case of 3-D optimization shown in fig. 5-6 fitness value is same but number of iterations of PSO are significantly less as compare to GA. For 2-D optimization, it can be seen from fig.8-9 that number of iterations of GA are slightly higher as compare to PSO.

Table 1 Comparison of Computational time of Genetic Algorithm(GA) and Particle Swarm Optimization (PSO)

		Computational Time(sec)	
Function Name	Dimension	GA	PSO
STYBLINSKI-TANG Function	1-D Optimization	0.10883	0.03538
	3-D Optimization	0.24811	0.08670
MICHALEWICZ Function	2-D Optimization	0.16130	0.06294

V. CONCLUSION

The two tests perform in this paper strengthen the hypothesis that both PSO and GA obtain the same high quality results but the computational effort needed by PSO to arrive such a superior quality results is relatively less when compared to the GA computational efforts. This computational efficiency superiority of PSO over GA can be observed from table 1 which increases as the dimension of search space increases. The analysis has also shown that the difference in computational effort between PSO and the GA is problem specific. It appears that PSO outperforms the GA in nonlinear problems with continuous design variables while GA is more efficient for discrete problems [13-14] or combinatorial design variables.

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