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Harmony Search and Firefly Optimization Algorithms Performance Analysis

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Abstract

Nature inspired algorithms are some of the efficient algorithms for solving optimization problems. Firefly and Harmony search algorithms are recent biologically inspired algorithm which have been used successfully in optimization problems. This paper aims to bring forward the comparative analysis between the harmony search algorithm and firefly algorithm. Initially, the general idea of firefly algorithm and harmony algorithm is discussed. Then, we have tested both the algorithms over non linear benchmark function. Finally, the results obtained from both the algorithms i.e. the respective convergence characteristic is compared and the result is discussed as per the scenarios.

1. Introduction

Over the last four decades, a large number of optimization algorithms have been developed. Many optimization problems in various fields have been solved using diverse optimization algorithms. Most of these algorithms are based on traditional mathematical techniques of numerical linear and nonlinear programming methods that usually seek to improve the solution in the neighborhood of a starting point [1]. Where as stochastic optimization is the general class of technique which employs some degree of randomness to find optimal solution for difficult problems. In order to comprehensively explore a wide design space, stochastic search techniques reveal their promising abilities in comparison with gradient-based optimization methods. Meta heuristics are the most general of these kinds of algorithms, and are applied to a very wide range of problems [2]. The numerical optimization algorithms provide a useful strategy to obtain the global optimum in simple and ideal models [1]. But many real-world engineering problems are highly non-linear and complex, often resulting into multiple local optima and quite difficult to solve using these algorithms [3,1].The computational drawbacks of existing numerical methods have forced researchers to rely on Meta heuristic algorithms based on simulations to solve engineering optimization problems [1]. Learning from naturally abundant biological systems and structures to design and develop a number of different kinds of optimization algorithms have been widely used in both theoretical study and practical applications. Therefore With the help of evolutionary concepts and behavior of biotic components of nature, many optimization algorithms have been developed [4]. Nature is a principal source of inspiration to propose new Metaheuristic optimization methods. Metaheuristic techniques are global optimization methods that attempt to reproduce natural phenomena or social behavior: for example, biological evolution, stellar evolution, thermal annealing, animal behavior, music improvisation, etc.[5]. Metaheuristics solve instances of problems that are believed to be hard in general, by exploring the usually large solution search space of these instances. These algorithms achieve result by reducing the effective size of the space and by exploring that space efficiently. Metaheuristics serve three main purposes: solving problems faster, solving large problems, and obtaining robust algorithms [2].

Intensification and diversification are important characteristics of the metaheuristic methods. Intensification searches around the current best solutions and selects the best candidate points. The diversification process allows the optimizer to explore the search space more efficiently, mostly by randomization. Such algorithms can increase the computational efficiency, solve larger problems, and implement robust optimization codes [3].Application of meta-heuristic techniques are gaining importance

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in identifying the best fit solution in a given search space. Intelligent, evolutionary and heuristic algorithms have been effectively used for many power system applications such as economic load dispatch, optimal power flow, unit commitment, hydro-thermal scheduling, security constrained optimal power flow, placement of capacitors in distribution systems etc [6]. Two of the nature inspired algorithm which have been mentioned here are harmony search and firefly algorithm. The Harmony Search algorithm is an evolutionary algorithm based on music composition, considering a process in which musicians improvise to create music. Its main characteristics are the simple concept, a few parameters and speed to find a solution [7]. In Harmony search, the harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques [8]. Firefly is one of the most recent meta-heuristic, nature-inspired, optimization algorithm, which is based on the behavior of fireflies, or lighting bugs including the light emission, light absorption and the mutual attraction[9,10].

The paper is organized as follows. In section 2 we provide the basic fundamentals of firefly algorithm. In section 3 information about harmony search is provided. In Section 4 nonlinear bench mark function are described. Section 5 consist of brief details about graph obtain from simulation performed using FFA and HSA on bench mark function mentioned in section 4 and brief comparison is made between both algorithms with the help of graphs. Finally in section 6 conclusions are drawn.

2. Firefly Algorithm

The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. The pattern of rhythmic flashes is often unique for a particular species. The flashing light can be formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate new optimization algorithms [11]. The Firefly Algorithm (FA) is a population-based algorithm to find the global optima of objective functions based on swarm intelligence, investigating the foraging behavior of fireflies [12].

Firefly algorithm (FFA) is a new Metaheuristic nature inspired. Although this algorithm has some similarities with other algorithms based on swarm intelligence such as GA, PSO, but FA has a number of special aspects which makes it different from these other well-known algorithm. Some of them are simple concept, easy implementation, less dependability on the adjusting parameters, real random characteristics, etc[13, 14].FFA has the advantage that it can find the global optima as well as the local optima simultaneously and effectively. A further advantage of FA is that different fireflies will work almost independently, it is thus particular suitable for parallel implementation. It is even better than GA and PSO because fireflies aggregate more closely around each optimum [15].The most prominent advantage is the use of the random movement of individuals, taking into account the mutual influence between individuals at the same time. Some recent literatures show that the algorithm is very effective in solving some optimization problems and can be better than the other traditional algorithms [14].

Fireflies are one of the most special creatures in nature. Most of fireflies produced short and rhythmic flashes and have different flashing behavior. Fireflies use these flashes for communication and attracting the potential prey [16]. Since the light intensity (brightness) is inversely proportional to the square of the distance from the light source (firefly) and a certain amount of light is absorbed by the air, fireflies are only visible up to a limited distance [17].They are believed to have a capacitor-like mechanism, that slowly charges until a certain threshold is reached, at which they re-lease the energy in the form of light, after which the cycle repeats [18]. In Firefly algorithm, there are three idealized rules: On the first rule, each firefly attracts all the other fireflies with weaker flashes. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex. Secondly, attractiveness is proportional to their brightness which is reverse proportional to their distances. For any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly. Finally, no firefly can attract the brightest firefly and it moves randomly [19].

The attractiveness β can be defined by:

$$\beta = \beta o e^{-\gamma r 2} \qquad (1)$$

Where r is the distance of two fireflies, b o is the attractiveness at r = 0 and g is the light absorption coefficient. The distance between two fireflies *i* and *j* at x i and x j, respectively, is determined using the following equation:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \qquad (2)$$

Where x *i*,*k* is the *k*-th parameter of the spatial coordinate x *i* of the *i*-th firefly. In the firefly algorithm, the movement of a firefly *i* towards a more attractive (brighter) firefly *j* is determined by the following equation:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha \epsilon_i \qquad (3)$$

Where the second term is related to the attraction, while the third term is randomization with the vector of random variables using a normal distribution [20]

3. Harmonic Search Algorithm

Geem-et-al developed a New Harmony search met heuristic algorithm that was conceptualized using the musical process of searching for a perfect state of harmony. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. The HS algorithm does not require initial values for the decision variables [21]. As the HS algorithm uses stochastic random search, derivative information is also unnecessary. The HS algorithm generates a new vector, after considering all of the existing vectors. These features increase the flexibility of the HS algorithm and produce better solution. In other Metaheuristic algorithms the harmony search algorithm imposes fewer mathematical requirements and can be easily adapted for solving various kind of engineering optimization problems. Furthermore numerical comparison demonstrates that the evolution in HS algorithm was faster than genetic algorithm [22].The effort to find the harmony in music is analogous to find the optimality in an optimization process. In other words, a musical improvisation process can be compared to search process in optimization; the pitch of each musical instrument determines the aesthetic quality just as the objective function value is determined by the set of values assigned to each decision variable [23]. The aesthetic quality of a musical instrument is essentially determined by its pitch, timber, and amplitude. In music theory, pitch p in MIDI is often represented as a numerical scale using the formula

$$p = 69 + 12\log_2(f/440) \quad (4)$$

Or

$$f = 440 \times 2^{(p-69)/12} \quad (5)$$

When a musician is improvising, he or she has three possible choices:

- Play any famous piece of music exactly from his or her memory;
- Play something similar to a known piece ;
- Compose new or random notes

To adjust the pitch slightly, we have to use a method such that it can adjust the frequency efficiently. In theory pitch can be adjusted linearly or nonlinearly, but in practice, linear adjustment is used. If $Xold$ is the current solution, then the new solution $Xnew$ is generated by

$$X_{new} = X_{old} + b_p(2\,\text{rand} - 1) \quad (6)$$

Where rand is a random number drawn from a uniform distribution [0, 1]. Here b_p is bandwidth, which controls the local range of pitch adjustment. Pitch adjustment is similar to mutation operator in genetic algorithms.

Harmony search could be potentially more efficient than genetic algorithms because harmony search does not use binary encoding and decoding, but it does have multiple solution vectors. Therefore the implementation of HS algorithm is easier. In addition, there is evidence to suggest that HS is less sensitive to the chosen parameters, which means that we do not have fine tune these parameters to get quality solutions [24].

In the HS algorithm, diversification is essentially controlled by the pitch adjustment and randomization -- here there are two subcomponents for diversification, which might be an important factor for the high efficiency of the HS method. The first subcomponent of playing a new pitch (or generating a new value) via randomization would be at least at the same level of efficiency as in other algorithms that handle randomization. However, an additional sub component for HS diversification is the pitch adjustment operation performed with the probability of rpa. Pitch adjustment is carried out by tuning the pitch within a given bandwidth. A small random amount is added to or subtracted from an existing pitch (or solution) stored in HM. Essentially, pitch adjustment is a refinement process of local solutions. Both memory consideration and pitch adjustment ensure that good local solutions are retained while the randomization makes the algorithm to explore global search space effectively. The subtlety is the fact that HS operates controlled diversification around good solutions, and intensification as well. The randomization explores the search space more widely and efficiently; while the pitch adjustment ensures that the newly generated solution is good enough, or not too far from existing good solutions [25].

The intensification in the HS algorithm is represented by the harmony memory accepting rate r accept. A high harmony acceptance rate means that good solutions from the history/memory are more likely to be selected or inherited. This is equivalent to a certain degree of elitism. Obviously, if the acceptance rate is too low, solutions will converge more slowly.

This algorithm has been successfully applied to various benchmark functions and real world optimization problems including parameter estimation of nonlinear Muskingum model and vehicle routing, design of water distribution networks and so on [26]. The HS algorithm is good at identifying the high performance regions of solution space within a reasonable time [27].

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4. Non-Linear Benchmark Functions

In order to validate any new optimization algorithm, we have to validate it against standard test functions so as to compare its performance with well established or existing algorithms. However various test function do exist, so new algorithm should be tested using at least a subset of functions with diverse properties so as to make sure whether or not the tested algorithm can solve certain type of optimization efficiently [28,29]. This section describes the eight well known nonlinear benchmark functions. These functions equation, range and optimum point are listed in table 1. Each benchmark function is independently run with both algorithms separately for hundred iterations for comparison. Table 1 shows the details of the Non-Linear Benchmark functions along with their ranges and optimum point.

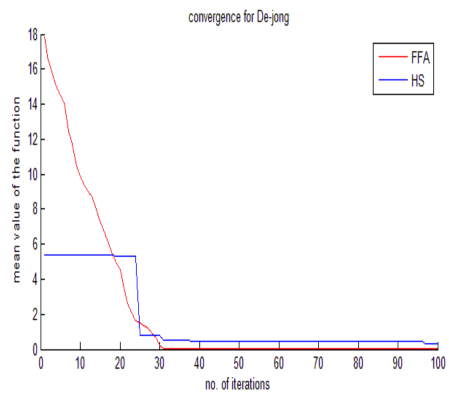

Fig: 1. Graph for De-jong function

Function	**Equation**	**Range**	**Optimum point**
De-jong's	F(x,y)= x^2+y^2	5.12<x,y <5.12	- (0,0)
Booth	F(x,y)= $(x+2y-7)^2+(2x+y-5)^2$	-10<x,y<10	(1,3)
Six-Hump Camelback	$F(x,y)=(4-2.1x^2+(1/3)x^4)x^2+xy+4(y^2-1)y^2$	-3<x<3	(0.0898,-0.7126)
Four Peak	$F(x,y)=(\|x\|+\|y\|)\exp[-0.0625(x^2+y^2)]$	-5<x,y<5	(0,0)
Matya's	$F(x,y)=0.26(x^2+y^2)-0.48xy$	10<x,y<10	(0,0)
Rosenbrock	F(x,y)= $(x-1)^2+100[(y-x^2)^2]$	-5<x,y<5	(1,1)
Beale	F(x,y)= $(1.5-x+xy)^2+(2.25-x+xy^2)^2+(2.625-x+xy^3)$	-4.5<x,y<4.5	(3,0.5)
Easom's	F(x,y)= $-\cos(x)\cos(y)*\mathrm{Exp}[-(x-\pi)^2-(y-\pi)^2]$	-100<x,y<100	(3.14,3.14)

Table: 1. Nonlinear Benchmark Function with their ranges and optimum points.

5. Simulation Result and Discussion

In order to compare the performance analysis of Firefly Algorithm and Harmony Search Algorithm, they have been implemented in MATLAB. Eight type of nonlinear benchmark function were used in performing simulation. Both the algorithms have been performed for 100 iteration. Result was summarized in tabular form mentioning the Elapsed time and mean time of both the algorithm for all eight bench mark function. Graphs of the simulation for different nonlinear benchmark functions are discussed below Figure 1 shows the characteristics of De-jong function. For HSA we observe a sudden step change at the starting, after few number of iteration there is sudden negative step change and HSA converges. For FFA, De-jong convergence is steep. Both the algorithms reach convergence almost after equal number of iteration but harmony search does not reach optimum value of function as at the latter stage the algorithm again show a small step change in the mean value of the function whereas FFA reaches optimum value.

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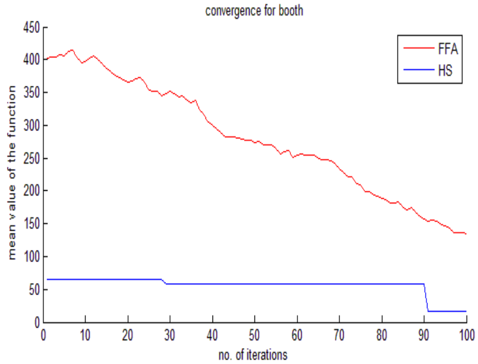

Fig 2: Graph forBooth function

Similarly for booth function, the HSA vary in step fashion for the search of optimum value of function and show convergence near end points of iteration,while for FFA optimum point wasn't reached for 100 iterations .

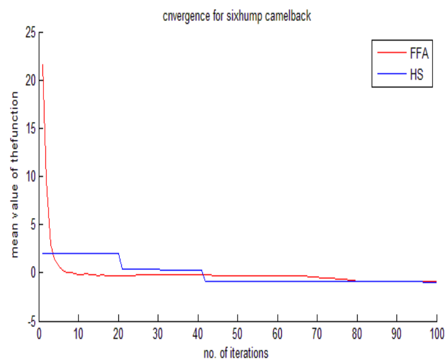

Fig: 3. Graph for Six Hump Camelback Function

The convergence of six hump camelback function for FFA is steep and faster, as it tends to converge at optimum point for smaller number iterations, whereas HSA show step variation and converges to optimum point for comparatively larger number of iteration

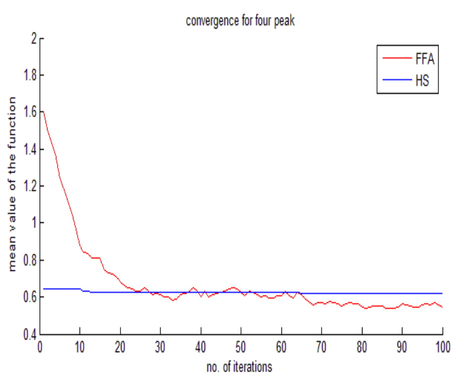

Fig 4: Graph for Four Peak Function

For Four Peak function, FFA show difficulty in reaching optimum point as it experience various fluctuation while for HSA the value of optimum point for mean value of the function, remain almost same throughout the run time of algorithm,therefore converges is much faster for HSA then for FFA. But FFA converges to better optimum point then HAS.

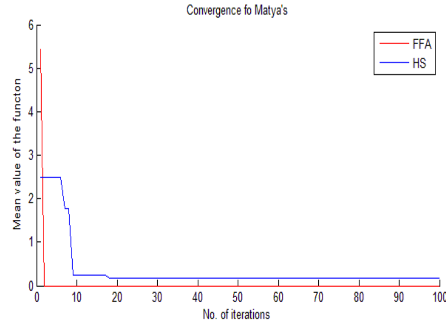

Fig: 5. Graph for Matya Function

The convergence of Matya function is found to be much faster with FFA than with HSA, as FFA take lesser number of iteration to reach at optimum point of convergence comparative to HSA.

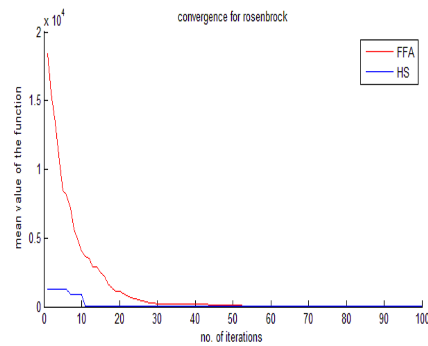

Fig: 6. Graph for Rosenbrock Function

For Rosenbrock function it is found that for HSA Converges faster than with FFA.As FFA reaches at optimum point for mean value of function for larger number of iterations.

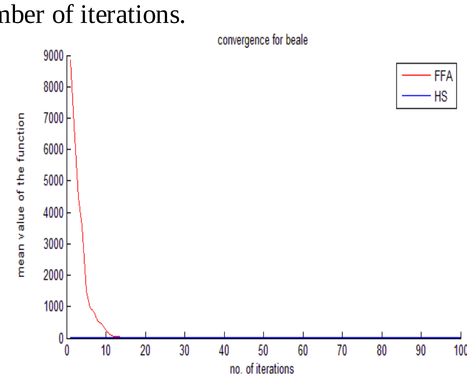

Fig: 7. Graph for Beale Function

The convergence of Beale function is found to be much faster with HSA, while FFA took time for finding optimum point. HSA found optimum solution in the starting of the iteration for HSA.

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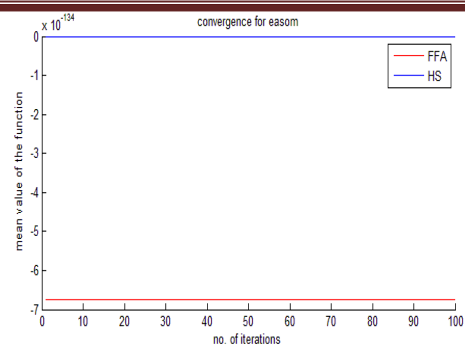

Fig: 8. Graph for Easom Function

The graph of Easom function shows that with FFA it was difficult to obtain optimum point for 100 iterations whereas HSA converges to optimum point quite faster and easily in the starting of the algorithm.

Function	Elapsed Time (Secs) FFA	Elapsed Time (Secs) HAS
De-jong	1.43	0.023
Booth	0.92	0.310
Six Hump Camelback	1.20	1.23
Four Peak	1.50	0.085
Matya's	1.45	0.062
Rosenbrock	1.050	0.610
Beale	0.81	0.661
Easom's	1.21	0.054

Table: 2. Performance of FFA and HSA

Table 2 shows Elapsed time of both the algorithms i.e. FFA and HSA for all eight non linear benchmark functions

6. Conclusion

Harmony search and firefly algorithms have been implemented for eight non linear bench mark functions. It has been observed that for almost all non linear benchmark functions FFA shows steep convergence while HSA converges to optimum point much easily and linearly. For Booth, Four peaks, Rosenbrock, Beale function and Easom function; HSA shows good response and is much faster than FFA. For these functions FFA does not converge even at optimum point. Whereas for De-jong, Six-Hump Camelback and Matya's function, the fireflies converge at optimum point for lesser number of iteration, therefore FFA is faster than HSA. For these three FFA finds better optimum point for mean value of function than HSA.

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