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GSA-BBO HYBRIDIZATION ALGORITHM

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ABSTRACT

In recent years, many heuristic optimization methods have been developed. Many of these methods are inspired by swarm behaviours in nature. In this paper, a new optimization algorithm based on newtons law of gravity and biogeography is introduced. In the proposed algorithm, the searching space of GSA is increased from local population range to global by using the concepts of biogeography. Also, the fitness of agents is optimized in GSA by using mathematical analysis.

Index Terms: GSA, BBO, GSA-BBO HYBRIDIZATION ALGORITHM,HSI,SIV

I INTRODUCTION

GSA(Gravitational Search Algorithm)

The hybridization of an algorithm pretends the algorithm more powerful and enhances the capabilities of an algorithm. Due to hybridization, coverage area of algorithms exacerbates and it can wrap more problems. The GSA is also hybridizes with conventional and swarm based algorithms to enhance its capabilities.

In solving optimization problems with a high-dimensional search space, the classical optimization algorithms do not provide a suitable solution because the search space increases exponentially with the problem size, therefore solving these problems using exact techniques (such as exhaustive search) is not practical. Over the last decades, there has been a growing interest in algorithms inspired by the behaviors of natural phenomena. It is shown by many researchers that these algorithms are well suited to solve complex computational problems such as optimization of objective function, pattern recognition, control objectives, image processing, filter modelling etc. Various heuristic approaches have been adopted by researches so far, for example Genetic Algorithm,Simulated Annealing, Ant Colony Search Algorithm ,Particle Swarm Optimization, etc.These algorithms optimization algorithms is an open problem.This algorithm is based on the Newtonian gravity:"Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them".

BBO(Biogeography Based Optimization)

The science of biogeography can be traced to the work of nineteenth century naturalists such as Alfred Wallace and Charles Darwin . Until the 1960s, biogeography was mainly descriptive and historical. In the early 1960s, Robert MacArthur and Edward Wilson began working together on mathematical models of biogeography, their work culminating with the classic 1967 publication, "*The Theory of Island Biogeography".*Mathematical models of biogeography describe how species migrate from one island to another, how new species arise, and

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how species become extinct. The term “island” here is used descriptively rather than literally. That is, an island is any habitat that is geographically isolated from other habitats. We therefore use the more generic term “habitat” in this paper (rather than “island”) . Geographical areas that are well suited as residences for biological species are said to have a high habitat suitability index (HSI) . Features that correlate with HSI include such factors as rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature. The variables that characterize habitability are called suitability index variables (SIVs). SIVs can be considered the independent variables of the habitat, and HSI can be considered the dependent variable.

Biogeography is nature’s way of distributing species, and is analogous to general problem solutions. Suppose that we are presented with a problem and some candidate solutions. The problem can be in any area of life (engineering, economics, medicine, business, urban planning, sports, etc.), as long as we have a quantifiable measure of the suitability of a given solution. A good solution is analogous to an island with a high HSI, and a poor solution represents an island with a low HSI. High HSI solutions resist change more than low HSI solutions. By the same token, high HSI solutions tend to share their features with low HSI solutions. (This does not mean that the features disappear from the high HSI solution; the shared features remain in the high HSI solutions, while at the same time appearing as new features in the low HSI solutions. This is similar to representatives of a species migrating to a habitat, while other representatives remain in their original habitat.) Poor solutions accept a lot of new features from good solutions. This addition of new features to low HSI solutions may raise the quality of those solutions.We call this new approach to problem solving biogeography-based optimization (BBO).

II STEPWISE GSA-BBO HYBRIDIZATION ALGORITHM

STEP-1:- Generate Initial Population

The gravitation is the tendency of masses to accelerate toward each other. It is one of the four fundamental interactions in nature (the others are: the electromagnetic force, the weak nuclear force, and the strong nuclear force). Every particle in the universe attracts every other particle. Gravity is everywhere. The inescapability of gravity makes it different from all other natural forces. The way Newton’s gravitational force behaves is called ‘‘action at a distance”. This means gravity acts between separated particles without any intermediary and without any delay. In the Newton law of gravity, each particle attracts every other particle with a ‘gravitational force’. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them:

$$F = G\frac{M_1 M_2}{R^2}, \tag{1}$$

where F is the magnitude of the gravitational force, G is gravitational constant, M_1 and M_2 are the mass of the first and second particles respectively, and R is the distance between the two particles. Newton’s second law says that when a force, F, is applied to a particle, its acceleration, a, depends only on the force and its mass, M :

$$a = \frac{F}{M}, \tag{2}$$

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Based on (1) and (2), there is an attracting gravity force among all particles of the universe where the effect of bigger and the closer particle is higher.

In addition, due to the effect of decreasing gravity, the actual value of the ‘‘gravitational constant depends on the actual age of the universe. Eq. (3) gives the decrease of the gravitational constant, G, with the age:

$$G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^{\beta}, \beta < 1, \tag{3}$$

Also, $G(t) = G_0 e^{\alpha t}$, (3.1)

constant at the first cosmic quantum-interval of time t_0 . G_0 is initial value of gravitational constant. Three kinds of masses are defined in theoretical physics:

Active Gravitational Mass, M_a, is a measure of the strength of the gravitational field due to a particular object. Gravitational field of an object with small active gravitational mass is weaker than the object with more active gravitational mass.

Passive Gravitational where G(t) is the value of the gravitational constant at time t. G(t_0) is the value of the gravitational Mass, M_p, is a measure of the strength of an object's interaction with the gravitational field. Within the same gravitational field, an object with a smaller passive gravitational mass experiences a smaller force than an object with a larger passive gravitational mass.

Inertial Mass, M_i, is a measure of an object resistance to changing its state of motion when a force is applied. An object with large inertial mass changes its motion more slowly, and an object with small inertial mass changes it rapidly.

Now, considering the above-mentioned aspects, we rewrite Newton's laws.

The gravitational force, f_{ij}, that acts on mass i by mass j, is proportional to the product of the active gravitational of mass j and passive gravitational of mass i, and inversely proportional to the square distance between them. a_i is proportional to f_{ij} and inversely proportional to inertia mass of i. More precisely, one can rewrite Eqs. (1) and (2) as follows:

$$f_{ij} = G \frac{M_{aj} \times M_{pi}}{R^2}, \tag{4}$$

$$a_i = \frac{F_{ij}}{M_{ii}}, \tag{5}$$

where M_{aj} and M_{pi} represent the active gravitational mass of particle i and passive gravitational mass of particle j, respectively, and M_{ii} represents the inertia mass of particle i.

Also, from BBO, We have

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Consider the probability P_s ,that the habitat contains exactly S species. P_s changes from time t to time $(t+\Delta t)$ as follows:

$$P_s(t+\Delta t) = P_s(t)(1-\lambda_s \Delta t - \mu_s \Delta t) + p_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \,, \quad (6)$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the habitat.

We assume that Δt is small enough so that the probability of more than one immigration or emigration can be ignored. Taking the limit of (6) as $\Delta t \to 0$ gives equation (7) shown at the bottom of the page. We define $n = S_{\max}$ and $P = [\mathrm{P}_0, \ldots, \mathrm{P}_n]^T$, for notational simplicity. Now, we can arrange the $\dot{P}_s$ equations (for S=0, ... ,n) into the single matrix equation

$$\dot{P} = AP, \quad (7)$$

Initialize Emigration rate 'E',Immigration rate 'I', $S_{\max}$, $m_{\max}$,Where

$$E = \lambda_k + \mu_k \text{,[when E=I]}, \quad (8)$$

Also, $$E = \frac{n\mu_k}{k} \,, \quad (9)$$

$$I = \frac{\lambda_k}{1-\frac{k}{n}} \,,$$

$$\text{(10} \Rightarrow I = \frac{n\lambda_k}{n-k} \,,$$

(11)

$$n = S_{\max} \,, \quad (12)$$

$$m_{\max} = \frac{m(s) \times P_{\max}}{1-P_s} \,, \quad (13)$$

Where $m_{\max}$ is user-defined parameter , m(s) is mutation rate and $P_{\max}$ is the solution probability.

$M_t = I + E$,[Adaptive learning step]

$m_i = [\mathrm{m}_{i1}, \mathrm{m}_{i2}, ..., \mathrm{m}_{is}]$

where, s is the dimension of problem

$\Rightarrow \mathrm{f}(\mathrm{m}_i)$ =f(m_{i1})+f(m_{i2})+......+f(m_{is})

Also,

m_{ti} =[($\mathrm{I}_{i1} + E_{i1}$)+($\mathrm{I}_{i2} + E_{i2}$)+.....+($\mathrm{I}_{is} + E_{is}$)]

Suppose, $m_i = M_t$

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$$\Rightarrow \frac{f_{ij}}{a_i} = I + E \,, \tag{14}$$

$$\frac{f_{ij}}{a_i} = \frac{n\lambda_k}{n-k} + \frac{n\mu_k}{k}$$

$$\Rightarrow f_{ij} = \frac{a_i n}{k(n-k)}[k\lambda_k + \mu_k(n-k)] \,, \tag{15}$$

$$\Rightarrow GSS = f_{ij}$$

Where GSS is the global search space factor.

Note:

$\rightarrow$This step is going to increase the search space of GSA .

$\rightarrow$As, GSA uses the local population range to collect sample mass items, but by using BBO, its searching space is going to increase by folds i.e; Global population range$\Rightarrow$Number of samples used in collecting information for processing increases$\Rightarrow$More optimal solutions$\Rightarrow$More optimization.

Step-2:- Randomized Initialization

To give a stochastic characteristic to our algorithm, we suppose that the total force that acts on agent i in a dimension d be a randomly weighted sum of dth components of the forces exerted from other agents:

$$f_i^d(t) = \sum_{j=1,\, j\neq i} rand_i \, f_{ij}^d \text{ (t)}, \tag{16}$$

where $rand_i$ is a random number in the interval [0, 1].

We remind that in order to avoid trapping in a local optimum the algorithm must use the exploration at beginning. By lapse of iterations, exploration must fade out and exploitation must fade in. To improve the performance of GSA by controlling exploration and exploitation only the Kbest agents will attract the others. Kbest is a function of time, with the initial value K_0 at the beginning and decreasing with time. In such a way, at the beginning, all agents apply the force, and as time

passes, Kbest is decreased linearly and at the end there will be just one agent applying force to the others. Therefore, Eq.(19) could be modified as:

$$f_i^d(t) = \sum_{j\in Kbest,\, j\neq i} rand_i \, f_{ij}^d(t) \,, \tag{17}$$

where Kbest is the set of first K agents with the best fitness value and biggest mass.

Also, initialize a random set of habitats, each habitat corresponding to a potential solution to the given problem.

STEP-3:- Fitness Evaluation Of Agents

Gravitational and inertia masses are simply calculated by the fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and walk more slowly. Assuming the

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equality of the gravitational and inertia mass, the values of masses are calculated using the map of fitness. We update the gravitational and inertial masses by the following equations:

$M_{ai} = M_{pi} = M_{ii} = M_i,$ i=1,2,3,...,N

$$M_{ai} = M_{pi} = M_{ii} = M_i, \tag{18}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}, \tag{19}$$

$$M_i = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \tag{20}$$

where $fit_i(t)$ represent the fitness value of the agent i at time t.

Calculate HSI,

i.e; HSI= $SIV_i + P_{os} + \lambda_k - \mu_k$, (21)

Where, HSI is Habitat Suitability Index, SIV is Suitability Index Variable and P_{os} is the original population size.

Using equations (9) and (10), We get

i.e; $HSI = SIV_i + P_{os} + \left[I\left(1 - \frac{k}{n}\right) - \frac{Ek}{n} \right]$

$$\Rightarrow HSI = SIV_i + P_{os} + \left[I - \frac{k(I+E)}{n} \right], \tag{22}$$

If I+E= M_t ,Then

$$\Rightarrow HSI = SIV_i + P_{os} + \left[I - \frac{kM_t}{n} \right],$$

(23) $\Rightarrow HSI = SIV_i + P_{os} + \left[I - \frac{kM_t}{S_{max}} \right],$

(24)

$[\because n = S_{max}]$

Where, $SIV_i = [SIV_{i1}, SIV_{i2}, ..., SIV_{is}]$, (25)

$$\Rightarrow f(SIV_i) = [f(SIV_{i1}) + f(SIV_{i2}) + ... + f_s(SIV_{is})]$$

As, HSI= $fit_i(t)$, (26)

Compare (22) and (28),We get

i.e; $fit_i(t) = SIV_i + P_{os} + \left[I - \frac{kM_t}{S_{max}} \right],$ (27)

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Substitute value of (30) in (22),We get

$$m_i(t) = \frac{S_{\max}\left[SIV + P_{os} \ + I - worst(t)\right] - km_t}{S_{\max}[best(t) - worst(t)]} \ , \tag{28}$$

STEP-4:-Update G(t), best(t), worst(t) and $M_i(t)$, for, i=1,2,3,...,N

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \tag{29}$$

For a Minimization Problem ,We have,

$$best(t) = \max_{j\in\{1,\ldots,N\}} fit_j(t), \tag{30}$$

$$worst(t) = \max_{j\in\{1,\ldots,N\}} fit_j(t), \tag{31}$$

STEP-5:-Calculation Of The Total Force In Different Directions

At a specific time 't', we define the force acting on mass 'i' from mass 'j' as following:

$$f_{ij}^{d}(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \in}, \tag{32}$$

where M_{aj} is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, G(t) is gravitational constant at time t, e is a small constant, and R_{ij} is the Euclidian distance between two agents i and j:

$$R_{ij}(t) = \left\| X_i(\mathrm{t}), \mathrm{X}_j(t) \right\|_2, \tag{33}$$

STEP-6:- Calculation Of Accelaration And Velocity

By the law of motion, the acceleration of the agent i at time t, and in direction dth, a_i^d (t), is given as follows:

$$a_i(t) = \frac{f_i(t)}{M_{ii}(t)}, \tag{34}$$

where M_{ii} is the inertial mass of ith agent.

Furthermore, the next velocity of an agent is considered as a fraction of its current velocity added to its acceleration.Therefore, its velocity could be calculated as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t), \tag{35}$$

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where $rand_i$ is a uniform random variable in the interval [0, 1]. We use this random number to give a randomized characteristic to the search.

For a Maximization Problem ,We have,

$$best(t) = \max_{j \in \{1,\ldots,N\}} fit_j(t) , \tag{36}$$

$$worst(t) = \min_{j \in \{1,\ldots,N\}} fit_j(t) , \tag{37}$$

The gravitational constant, G, is initialized at the beginning and will be reduced with time to control the search accuracy. In other words, G is a function of the initial value (G_0) and time (t):

$$G(t) = G(G_0, t) , \tag{38}$$

STEP-7:- **Updating Agents Position**

We have,

$$x_i^d(t+1) = v_i^d(t) + v_i^d(t+1) , \tag{39}$$

STEP-8:- Repeat steps (3) and (4), Until the stop criterion is reached.

STEP-9:- Stop.

III PRINCIPLE OF GSA-BBO HYBRIDISATION ALGORITHM

To see how the proposed algorithm is efficient some remarks are noted:

– Since each agent could observe the performance of the others, the gravitational force is an information-transferring tool.

– Due to the force that acts on an agent from its neighborhood agents, it can see space around itself.

– A heavy mass has a large effective attraction radius and hence a great intensity of attraction. Therefore, agents with a higher performance have a greater gravitational mass. As a result, the agents tend to move toward the best agent.

– The inertia mass is against the motion and make the mass movement slow. Hence, agents with heavy inertia mass move slowly and hence search the space more locally. From BBO, Immigration and Emigration concepts are used to modify existing islands of habitats. So, these can be considered as adaptive learning steps.

– Gravitational constant adjusts the accuracy of the search, so it decreases with time (similar to the temperature in a Simulated Annealing algorithm).

From BBO, HSI and SIV are used to create accurate habitats of species, creating species diversity.

– GSA-BBO is a memory-less algorithm. However, it works efficiently like the algorithms with memory. Our experimental results show the good convergence rate of the GSA.

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– Here, we assume that the gravitational and the inertia masses are the same. However, for some applications different values for them can be used. A bigger inertia mass provides a slower motion of agents in the search space and hence a more precise search. Conversely, a bigger gravitational mass causes a higher attraction of agents. This permits a faster convergence.

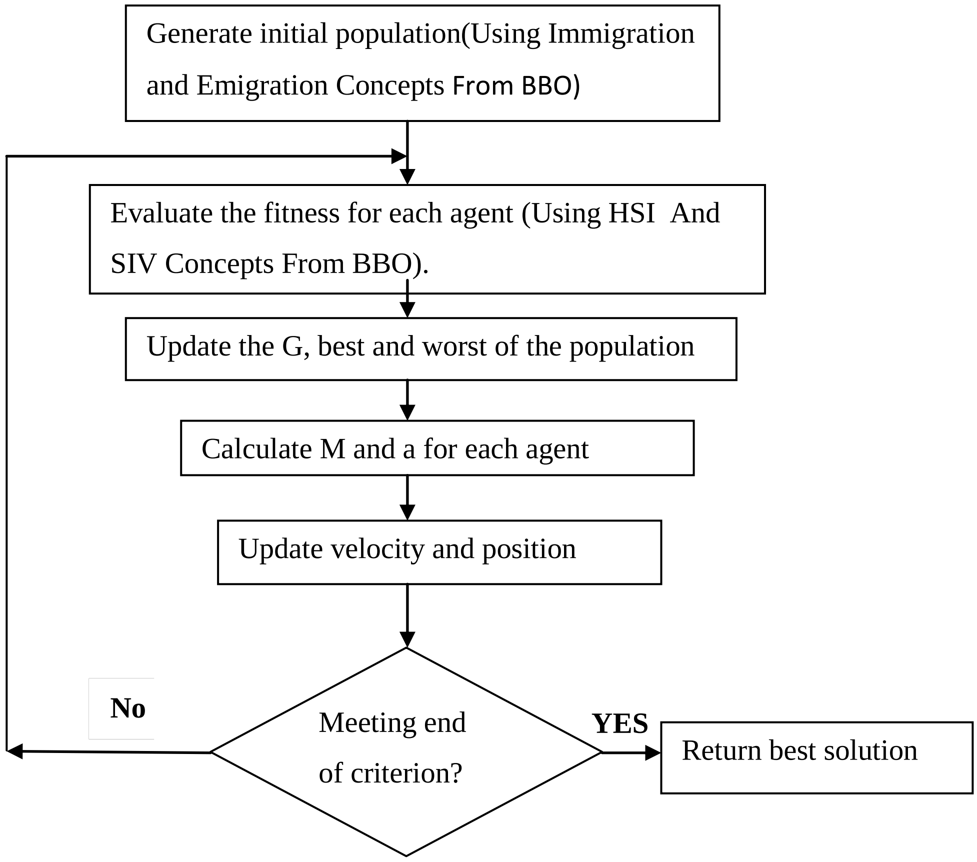

Fig. 1. General Principle Of GSA-BBO Hybridisation Algorithm

IV COMPARATIVE STUDY

In this section, to see how GSA-BBO is situated comparing other heuristic search algorithms, we compare GSA-BBO with PSO, RGA and GSA. First, the tables of comparision are given and then some implementation outputs are given.

Table 1

Minimization result of benchmark functions(F_1 to F_7) with n = 30. Maximum number of iterations = 1000.

Test Function	RGA	PSO	GSA	GSA-BBO
F_1	23.13	1.8×10^{-3}	1.4408×10^{-17}	1.005×10^{-17}
F_2	21.87	1.2×10^{-3}	2.8707×10^{-8}	2.3515×10^{-8}
F_3	$5.6\times10^{+3}$	$4.1\times10^{+3}$	446.8342	224.5238

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F_4	11.78	8.1	2.3137×10^{-9}	2.8518×10^{-9}
F_5	$1.1\times10^{+3}$	$3.6\times10^{+4}$	26.1268	25.8640
F_6	24.01	1.0×10^{-3}	0	0
F_7	0.06	0.04	0.0163	0.0100

Table 2

Minimization result of benchmark functions(F_8 to F_{13}) with n = 30. Maximum number of iterations = 1000.

Test Function	RGA	PSO	GSA	GSA-BBO
F_8	$-1.2\times10^{+4}$	$-9.8\times10^{+3}$	$-2.3986\times10^{+3}$	$-2.6655\times10^{+3}$
F_9	5.90	55.1	10.9445	15.9193
F_{10}	2.13	9.0×10^{-3}	3.9149×10^{-9}	3.5582×10^{-9}
F_{11}	1.16	0.01	2.6345	2.0185
F_{12}	0.051	0.29	1.538×10^{-19}	1.3076×10^{-19}
F_{13}	0.081	3.1×10^{-18}	3.2900×10^{-18}	1.6858×10^{-18}

Table 3

Minimization result of benchmark functions in (F_{14} to F_{23}) . Maximum number of iterations = 500

Test Function	RGA	PSO	GSA	GSA-BBO
F_{14} n=2	0.998	0.998	6.8563	2.0769
F_{15} n=4	4.0×10^{-3}	2.8×10^{-3}	0.0025	0.0034
F_{16} n=2	–1.0313	–1.0316	–1.0316	–1.0316
F_{17} n=2	0.3996	0.3979	0.3979	0.3979
F_{18} n=2	5.70	3.0	3.0000	3.0000
F_{19} n=3	–3.8627	–3.8628	–3.8628	–3.8628
F_{20} n=6	–3.3099	–3.2369	–3.3220	–3.3220
F_{21} n=4	–5.6605	–6.6290	–3.9228	–10.1532
F_{22} n=4	–7.3421	–9.1118	–10.4029	–10.4029
F_{23} n=4	–6.2541	–97.634	–10.5364	–10.5364

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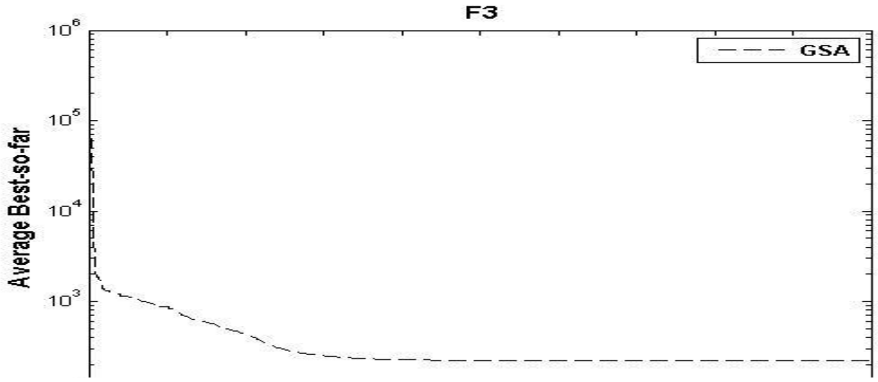

Fig. 2. Performance of GSA for minimization of F_3 with n = 30.

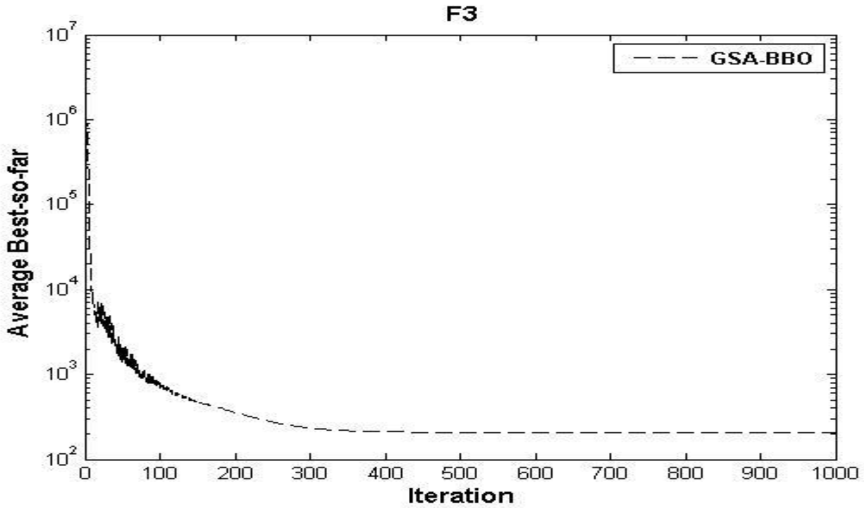

Fig. 3. Performance of GSA-BBO for minimization of F_3 with n = 30.

V CONCLUSION

This paper presents the hybridization of Gravitational Search Algorithm and Biogeography Based Optimization.I have used the mathematical analysis, in order to find the optimization equations which can be used to increase the functionality of GSA.In GSA, we have an isolated system of masses. Using the gravitational force, every mass in the system can see the situation of other masses. The gravitational force is therefore a way of transferring information between different masses.I have used the Biogeography, the study of the geographical distribution of biological species, it can be used to derive algorithms for optimization. The concepts which I have used are Immigration, Emmigration, HSI,SIV,etc. This paper is preliminary in nature and, therefore, opens up a wide range of possibilities for further research.

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