I.J. Intelligent Systems and Applications, **2016, 11, 34-50**
Published Online November 2016 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijisa.2016.11.05

Improved Krill Herd Algorithm with Neighborhood Distance Concept for Optimization

Prasun Kumar Agrawal[1], Manjaree Pandit[1], Hari Mohan Dubey[*1]
Department of Electrical Engineering, [1]M.I.T.S, Gwalior, India
*Corresponding Author, Tel.+91-0751-2665962, +91-0751-2409348, E-mail: harimohandubeymits@gmail.com

Abstract—Krill herd algorithm (KHA) is a novel nature inspired (NI) optimization technique that mimics the herding behavior of krill, which is a kind of fish found in nature. The mathematical model of KHA is based on three phenomena observed in the behavior of a herd of krills, which are, moment induced by other krill, foraging motion and random physical diffusion. These three key features of the algorithm provide a good balance between global and local search capability, which makes the algorithm very powerful. The objective is to minimize the distance of each krill from the food source and also from the point of highest density of the herd, which helps in convergence of population around the food source. Improvisation has been made by introducing neighborhood distance concept along with genetic reproduction mechanism in basic KH Algorithm. KHA with mutation and crossover is called as (KHAMC) and KHA with neighborhood distance concept is referred here as (KHAMCD). This paper compares the performance of the KHA with its two improved variants KHAMC and KHAMCD. The performance of the three algorithms is compared on eight benchmark functions and also on two real world economic load dispatch (ELD) problems of power system. Results are also compared with recently reported methods to establish robustness, validity and superiority of the KHA and its variant algorithms.

Index Terms—Krill Herd Algorithm (KHA), mutation and crossover, neighborhood distance concept, unimodal function, multimodal function, economic load dispatch.

I. INTRODUCTION

Optimization is basically a spontaneous process that plays an important role in real world application. Its objective is to compute a set of variables that either minimize or maximize the objectives function within given constraints. For solution of a given model or an objective function, there is a need of efficient optimization techniques which can either be conventional (deterministic) or have a stochastic, evolutionary approach. Conventional techniques include nonlinear programming, linear programming, quadratic programming, Newton's method etc. Deterministic approaches generally require an initial guess which has a vital impact on the final solution. Considering practical utility of optimization there is need of robust and efficient algorithms which are free from this limitation.

Generally the practical problems are much complex and also have many constraints which cannot be solved by conventional approaches. On the other hand, nature inspired methods which are basically population based stochastic search techniques often provides quick and reasonable solution; though a careful tuning of parameters is required to prevent solution from getting trapped in local minima. In the recent years various population based evolutionary techniques have been developed for solution of problems related to real world application.

Among evolutionary algorithms genetic algorithm (GA) is probably the most popular algorithm based on Darwinian evolution concept proposed by Holland in 1992[1]. Simple concepts are involved in it and involvement of stochastic operators may be the key point for popularity of this algorithm. After GA various nature inspired algorithms have been proposed such as Particle Swarm Optimization(PSO)[7], Ant Colony Optimization(ACO)[8], Harmony Search Algorithm (HSA)[9], Artificial Bee Colony Algorithm(ABC)[15], Gravitational Search Algorithm(GSA)[16] etc, which may be based on natural concepts of evolution, collective behavior, ecology or physical science [2-26] listed in Table 1. Each algorithm has its own advantage. But the key points associated with evolutionary algorithms which make them popular for solution of complex constrained problem in comparison to conventional approach are depicted in Table 2. In fact there is no optimization technique has been developed that can capable to solve all types of optimization problems [27]. A comparative study of NI algorithms for unimodal and multimodal optimization problem is presented in ref. [55].

Among NI algorithms krill herd algorithm (KHA) is novel optimization techniques that inspired by herding behavior of krill herd. KHA implemented to solve different types of real world optimization problems either by hybridizing with other evolutionary algorithm to improve the basic KHA or by adding some mathematical concept [28-38]. Variant of KHA proposed till date is depicted in Fig. 1. In this paper KHA with neighborhood distance concept is proposed and their performances were analyzed using benchmark functions and practical complex constrained problems related to economic load dispatch (ELD) of power system.

This paper organized as below: section I deals with introduction to optimization techniques, section II presents krill herd algorithm and its variants. The performance evaluation on numerical benchmarks and using standard complex constrained test cases of ELD are presented in section III and IV respectively. Finally concluding remarks are presented in section V.

Table 1. Development of Nature Inspired (NI) Algorithms in Chronological Order

Year	Name	Year	Name
1966	Evolution Strategies [2]	2007	Firefly Algorithm [14]
1966	Evolutionary Programming [3]	2007	Artificial Bee Colony Algorithm [15]
1975	Genetic Algorithms [1]	2009	Gravitational Search Algorithm [16]
1979	Cultural Algorithms [4]	2010	Bat Algorithm [17]
1983	Simulated Annealing [5]	2011	Cuckoo Search Algorithm [18]
1989	Tabu Search [6]	2012	Krill Herd Algorithm [19]
1995	Particle Swarm Optimization [7]	2013	Social Spider optimization [20]
1996	Ant Colony Optimization [8]	2013	Backtracking Search Algorithm [21]
2001	Harmony Search Algorithm [9]	2014	Grey Wolf Optimization [22]
2002	Estimation of Distribution Algorithm [10]	2014	Symbiotic organism Search Algorithm [23]
2002	Bacterial Foraging Algorithm [11]	2015	Lion Optimization Algorithm [24]
2005	Honey Bee Mating Optimization Algorithm [12]	2015	Stochastic fractal Search [25]
2007	Intelligent Water Drops [13]	2015	Lightening Search [26]

Table 2. Comparison of Traditional & Evolutionary Technique

Traditional Technique	Evolutionary Technique
Single point search	Population based search
Gradient search	Random search
Deterministic algorithm	Stochastic algorithm
Mathematical principle	Natural & physical based
Fast but will not run for many problems.	Slow but run for most of the real world problem, complex and undefined problems.
Same solution every time	Different solution with time accuracy.
Different solver required for different function.	Independent of objective functions.

II. Krill Herd Algorithm and its Modules

Krill is a species of fish which are generally found in oceans. Based on the breeding mechanism, they have the ability to form large swarm population. KHA mimics the collective behavior of krill swarm considering their self-position as well as their position in group. During optimization the global optima solution refers the minimum distance of a krill individual from highest density food source whereas individual krill try to migrate near the best solution.

A. Lagrangian model of Krill Herd Algorithm (KHA)

The fitness function combines position of individual krill from food source and density of krill around the food source. The movement of each krill in two dimensional search spaces can be evaluated on the basis of movement of other krill, foraging activity and the physical diffusion process.

1) Motion induced by other krill individual

Maintaining high density is essential to get optimal solution in KHA because the fitness function highly influenced by density of krill in search space. The direction of krill movement is computed on the basis of local swarm density, target swarm density and repulsive swarm density as it highly influenced by neighboring krill. Considering all effects simultaneously velocity of movement for i^{th} krill can be expressed as [19, 46]:

$$v_i^{new} = v^{\max}\sigma_i + \omega_n \times v_i^{old} \tag{1}$$

Where $v^{\max}$ are the motion induced by other krill, v_i^{new} & v_i^{old} are the motion induced by ith krill at modified as well their previous movement and ω_n is the inertia weight for induced motion.

The direction of motion (σ_i) of i^{th} krill can be expressed as:

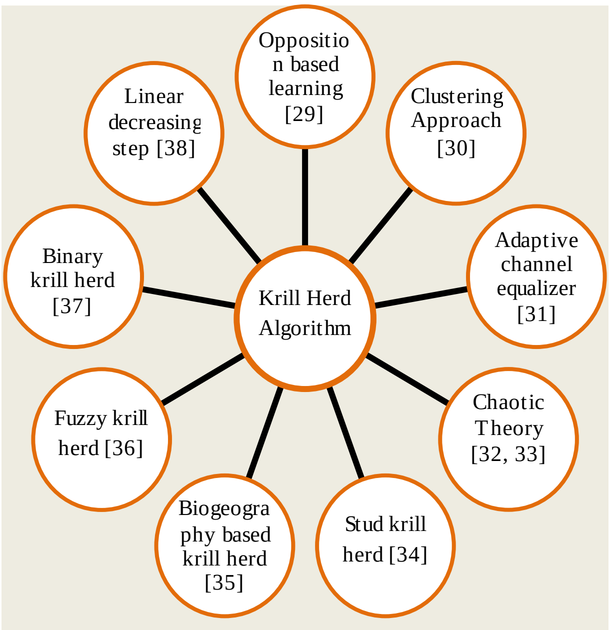


Fig.1. Variants of Krill Herd Algorithm

$$\sigma_i = \sum_{j=1}^{nb}\left[\frac{f_i - f_j}{f^{worst} - f^{best}} \times \frac{K_j - K_i}{|K_j - K_i| + rand(0,1)}\right] + 2\times\left[rand(0,1) + \frac{iter}{iter^{\max}}\right] f_i^{best} x_i^{best} \tag{2}$$

Where f_i, f_j are the fitness of i^{th} and j^{th} krill, f_i^{worst}, f_i^{best} are the worst and best fitness among krill swarm and *nb* is the total number of neighbor.

Selection of neighbor is based on the distance senesced (*ds*) by each krill, it is defined as:

$$ds_i = \frac{i}{5N}\sum_{k=1}^{N}|K_i - K_k| \tag{3}$$

Where *N* is the number of krill (population size) and K_i, K_k are the position of i^{th} and k^{th} of krill respectively.

2) Foraging motion

Movement of krill individual is guided by location of food and the past experience of food location, in algorithm this step helps to update position of best krill individual. The foraging motion of i^{th} krill at its q^{th} moment (v_{fi}^{q}) can be expressed as [19, 46]:

$$v_{fi}^{q} = 0.02\times\left[2\left(1-\frac{iter}{iter_{\max}}\right) f_i \frac{\sum_{i=1}^{N}\frac{x_i}{k_i}}{\sum_{i=1}^{N}\frac{1}{k_i}} + f_i^{best} x_i^{best}\right] + \omega_x V_{fi}^{q-1} \tag{4}$$

Where ω_x represents the foraging motion.

3) Diffusion

The diffusion of the krill individual is considered to be a random in nature and it is incorporated to enhance the population diversity. The diffusion speed can be expressed as:

$$v_{di} = v_d^{\max}\varphi \tag{5}$$

Where $v_d^{\max}$ is the maximum diffusion speed and ϕ is the random directional vector uniformly distributed between (-1, 1) [19].

4) Position Update mechanism

During optimization process krill regularly changes their position in search space guided by motion induced by other krill individual, foraging motion and diffusion. All motion work simultaneously and makes algorithm more powerful. Position Update mechanism of i^{th} krill can be expressed as [19, 46]:

$$x_i^{q+1} = x_i^q + \left(v_i^q + v_{fi}^q + v_{di}^q\right)\times\eta\times\sum_{j=1}^{M}\left(ub_i - lb_j\right) \tag{6}$$

Where ub_i, lb_j the upper and lower limits of j^{th} variable, *M* is the total number of variable and $\eta \in (0,2)$ is a constant.

The position of krill individual is updated on the basis of their fitness, and stops as global optimal solution/ termination criteria achieved.

Also, in order to boost the exploration as well as exploitation capacity of KHA, Crossover and mutation operator as in differential evolution has been introduced here.

B. KrillHerd Algorithm with Mutation and Crossover (KHAMC)

1) Crossover operator

Krill individual position is updated on the basis of crossover probability. Updating procedure of the j^{th} components of the i^{th} krill may be described as:

$$x_{i,j} = \begin{cases} x_{r,j} & if \quad rand \le Cr \\ x_{i,j} & if \quad rand > Cr \end{cases} \quad \text{where r = 1,2,3….N} \tag{7}$$

$$Cr = 0.2\times f_i^{best} \tag{8}$$

The crossover probability decreases as fitness increases, for global best solution *Cr* = 0.

2) Mutation operator

$$x_{i,j} = x_{best,j} + F\left(x_{1,j} - x_{2,j}\right), F\in(0,1) \tag{9}$$

With the help of mutation probability (P_m) the modified value selected as:

$$x_{i,j}^{new} = \begin{cases} x_{r,j} & if \quad rand \le P_m \\ x_{i,j} & if \quad rand > P_m \end{cases} \quad \text{where r = 1,2,3….N} \tag{10}$$

$$\text{and} \quad P_m = 0.05 / f_i^{best} \tag{11}$$

C. KrillHerd Algorithm with Neighborhood Distance Concept (KHAMC)

In order to improve the computational time, neighboring distance concept has been added here. Here distance of individual krill from their neighboring krill ($dis_{i,o}$) can be computed as:

$$dis_{i,o} = \left\| x_i - x_o \right\| \tag{12}$$

The distances so obtained are arranged in an ascending order and their respective index positions are computed. Now shorted top twenty five percent of the actual population used for computing motion induced by other krill individual and then for local swarm density calculation. This process helps to further improve the exploitation capability of KHAMC.

To analyze the performance of KHAMCD, it is tested on unimodal / multimodal benchmark functions along with two real world optimization problem of power system.

III. Performance Evaluation

All experiments were conducted on a PC with 1.80 GHz Intel i5 processor and 4.00 GB RAM. Our implementation was compiled using MATLAB. Implementation procedure of proposed algorithm for solution of problem is depicted in Fig.2. In order to examine the performance KHAMCD, it is tested on eight benchmark functions [39] as in Table 3. Further its applicability and validity is investigated using two complex constrained real world optimization problems of economic load dispatch. Comparison of results made with recent reported method to show superiority of algorithm.

A. Parameter setup

Simulation analysis were carried out with foraging speed (v_f) = 0.02, the maximum induced speed (v^{max}) = 0.01, crossover probability (Cr) = 0.9, probability of mutation (P_m) = 0.6. The inertia weights (ω) are set at 0.9 at the beginning whereas 0.1 at the end and the constant (η) set at 0.2. The diffused speed considered as V_d^{max} = 0.010 which decreases linearly to 0.002 as algorithm reaches to termination criteria as maximum iteration.

B. Testing of Benchmark Function

All experiment was conducted with population size of 100 over 20 trials. Maximum iteration 100 is used for benchmark function (*f1*, *f2*, *f4*, *f6*, *f7*, *f8*) and 300 for (*f3*) and 500 for (*f5*).The outcome of simulation of benchmark obtained for KHA, KHAMC and KHAMCD in terms of best fitness, worst fitness, mean fitness, standard deviation (SD) and the computational time listed in Table 4. The results are also compared with different reported results in recent literature as chaotic KHA [32, 33], fuzzy KHA [36], and KHAL [38]. Here it is observed that KHAMCD performs better in consistent manner for all problems.

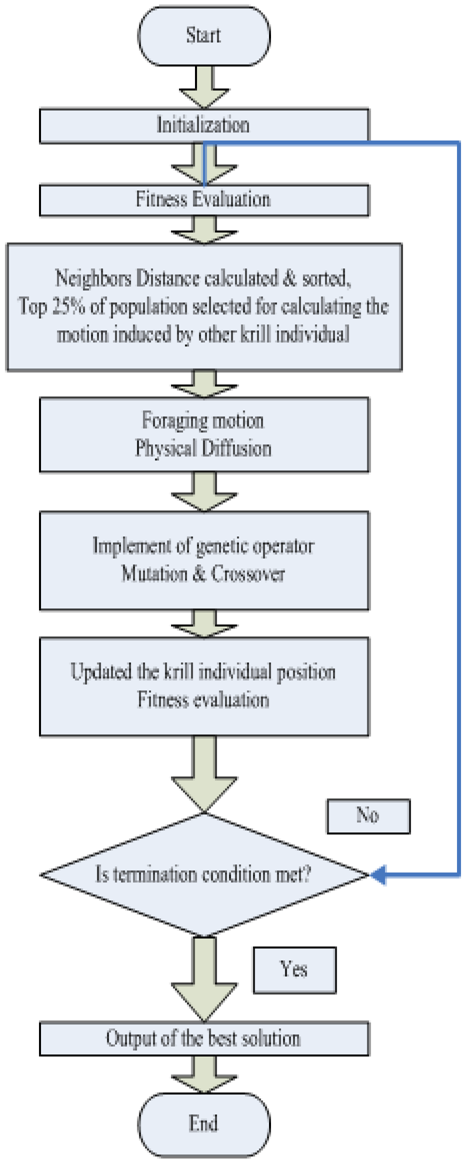


Fig.2. Flowchart of KH Algorithm with neighborhood distance concept

Table 3. Benchmark Functions

Function Name	Dimension	Type	Range	Definition	Solution
Griewank	30	Continuous, differentiable, non-separable, scalable, multimodal	[-100,100]	$f_1 = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}}) + 1$	*f(x)=0*
Ackley	30	Continuous, differentiable, non-separable, scalable, multimodal	[-35,35]	$f_2 = 20 + e - 20e^{-\frac{1}{5}\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}} - e^{-\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)}$	*f(x)=0*
Booth	30	Continuous, differentiable, non-separable, non-scalable, unimodal	[-10,10]	$f_3 = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$	*f(x)=0*
Rastrigin	30	Continuous, differentiable, separable, multimodal	[-5.12,5.12]	$f_4 = 10D + \sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i))$	*f(x)=0*
Alpine	30	Continuous, Non-differentiable, separable, scalable, multimodal	[-10,10]	$f_5 = \sum_{i=1}^{D} \lvert x_i \sin(x_i) + 0.1x_i \rvert$	*f(x)=0*
Schwefel	30	Continuous, differentiable, separable, scalable, multimodal	[-500,500]	$f_6 = -\frac{1}{D}\sum_{i=1}^{D} x_i \sin\sqrt{\lvert x_i \rvert}$	*f(x)*=-418.983
Sphere	30	Continuous, differentiable, separable, scalable, multimodal	[-5.12,5.12]	$f_7 = \sum_{i=1}^{D} x_i^2$	*f(x)=0*
Rosenbrock	30	Continuous, differentiable, non-separable, scalable, unimodal	[-2, 2]	$f_8 = \sum_{i=1}^{D-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right]$	*f(x)=0*

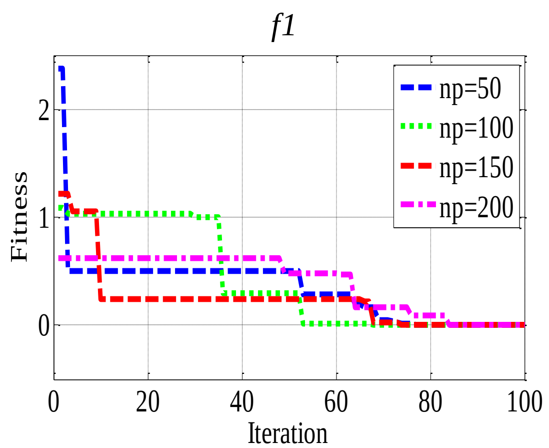
Table 4. Statistical Performance of KH variants on Benchmark Problem

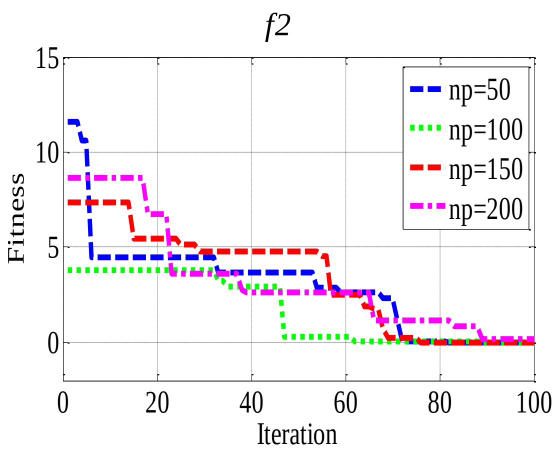
Function	D	Method	N	Imax	Best fitness	Worst fitness	Mean fitness	SD	CPU Time (sec)
f_1	2	KHA	100	100	1.2309x10-2	3.8590x10-1	1.2919x10-1	2.0732x10-2	10.28
		KHAMC	100	100	1.6069x10-7	2.4664x10-3	4.3616x10-4	1.5072x10-4	10.24
		KHAMCD	100	100	**4.6781x10-9**	**8.7742x10-4**	**5.1675x10-5**	**4.2523x10-5**	**7.29**
	20	KHA	100	100	3.2079x10-4	2.3175x10-1	8.4477x10-2	1.7268x10-2	10.38
		KHAMC	100	100	1.7128x10-6	2.1404x10-3	3.1334x10-4	1.1908x10-4	10.37
		KHAMCD	100	100	**5.2389x10-10**	**5.5851x10-4**	**5.0677x10-5**	**2.8277x10-5**	**7.37**
	30	KHA	100	100	5.6578x10-4	3.8556x10-1	5.9577x10-2	1.9901x10-2	10.43
		KHAMC	100	100	2.1187x10-8	7.2481x10-3	1.0649x10-3	4.2692x10-4	10.51
		KHAMCD	100	100	**3.1535x10-9**	**1.7069x10-3**	**1.4858x10-4**	**8.9533x10-5**	**7.74**

Function	D	Method	N	Imax	Best fitness	Worstfitness	Mean fitness	SD	CPU Time (sec)
		Fuzzy KHA [36]	25	200	2.12x10-8	-------	1.5462x10-2	-------	-------
		Choatic KHA [32]	------	500	-------	-------	5.6939x10-2	2.6886x10-2	-------
		Choatic KHA [33]	25	200	1.32x10-7	-------	1.44x10-2	-------	-------
		KHAL [38]	10	10000	-------	-------	4.1x10-3	6.8x10-3	-------
f_2	2	KHA	100	100	2.7450	1.2069x10+1	7.5091	6.4341x10-1	10.48
		KHAMC	100	100	1.8975x10-3	1.6410x10-1	4.9798x10-2	9.3817x10-3	10.33
		KHAMCD	100	100	**2.7828x10-5**	**2.0834x10-2**	**4.0406x10-3**	**1.4270x10-3**	**7.33**
	20	KHA	100	100	2.2341	1.2621x10+1	6.7996	6.0828x10-1	10.39
		KHAMC	100	100	2.9504x10-2	1.7021x10-1	7.1720x10-2	8.0913x10-3	10.44
		KHAMCD	100	100	**1.2246x10-4**	**2.3592x10-2**	**3.2265x10-3**	**1.3799x10-3**	**7.23**
	30	KHA	100	100	1.5591	1.5017x10+1	7.4434	8.0605x10-1	10.35
		KHAMC	100	100	5.8713x10-3	3.2497x10-1	6.8098x10-2	1.5643x10-2	10.43
		KHAMCD	100	100	**1.0746x10-5**	**4.8179x10-2**	**6.7143x10-3**	**2.4956x10-3**	**7.35**
		Fuzzy KHA [36]	25	200	1.119x10-4	-------	3.3439x10-1	-------	-------
		Choatic KHA [33]	25	200	1.268x10-4	-------	1.8594x10-1	-------	-------
		KHAL [38]	10	10000	-------	-------	6.523x10-1	2.323x10-1	-------
f_3	2	KHA	200	300	2.2981x10-3	**2.8530x10-1**	6.0273x10-2	**1.4454x10-2**	120.56
		KHAMC	200	300	**9.7826x10-6**	8.6048x10-1	7.7090x10-2	4.7057x10-2	120.81
		KHAMCD	200	300	4.2118x10-5	4.5324x10-1	**4.9316x10-2**	2.3785x10-2	**105.88**
	20	KHA	100	300	3.6026x10-4	**3.1339x10-1**	9.8358x10-2	**2.3722x10-2**	30.48
		KHAMC	100	300	1.9298x10-5	6.5852x10-1	7.5571x10-2	3.5505x10-2	30.83
		KHAMCD	100	300	**8.4031x10-6**	9.3225x10-1	**6.4951x10-2**	4.5088x10-2	**21.77**
f_4	2	KHA	100	100	3.3561x10-5	6.4810x10-1	8.4018x10-2	3.4771x10-2	10.23
		KHAMC	100	100	3.6062x10-6	1.0730x10-2	1.7521x10-3	5.1410x10-4	10.06
		KHAMCD	100	100	**3.2963x10-7**	**1.7130x10-3**	**3.2657x10-4**	**9.5710x10-5**	**7.19**
	20	KHA	100	100	1.3061x10-3	6.2422x10-1	6.8567x10-2	2.9756x10-2	10.21
		KHAMC	100	100	7.3550x10-6	3.5432x10-2	8.3993x10-3	1.9862x10-3	10.19
		KHAMCD	100	100	**1.4927x10-7**	**1.6322x10-3**	**2.6607x10-4**	**8.5491x10-5**	**7.49**
	30	KHA	100	100	1.1504x10-5	7.2139x10-1	9.1691x10-2	3.9918x10-2	10.45
		KHAMC	100	100	1.4198x10-4	8.1789x10-2	1.3374x10-2	4.9771x10-3	10.41
		KHAMCD	100	100	**1.4273x10-5**	**4.1291x10-3**	**5.1064x10-4**	**2.3012x10-4**	**7.63**
		Fuzzy KHA [36]	25	200	1.025096	-------	3.980158	-------	-------
		Choatic KHA [32]	------	500	-------	-------	20.50905	4.3942	-------
		Choatic KHA [33]	25	200	3.072x10-2	-------	2.6523x10-1	-------	-------
		KHAL [38]	10	10000	-------	-------	9.6714	6.5899	-------
f_5	2	KHA	100	500	5.4811x10-4	1.4929x10-1	3.3880x10-2	7.5166x10-3	50.56
		KHAMC	100	500	5.2634x10-6	4.9520x10-4	9.1777x10-5	3.0892x10-5	51.08
		KHAMCD	100	500	**2.2140x10-9**	**9.5300x10-8**	**2.8705x10-8**	**4.7439x10-9**	**35.57**
	20	KHA	100	500	1.8992x10-3	**1.8324**	**1.2769x10-1**	**8.7695x10-2**	51.33
		KHAMC	100	500	5.8783x10-1	26.097	5.5406	1.2903	51.30
		KHAMCD	100	500	**1.6978x10-4**	12.678	2.9513	8.6842x10-1	**35.83**
f_6	2	KHA	100	100	-726.68	-597.23	-661.66	8.353	10.20
		KHAMC	100	100	**-837.97**	-716.75	**-824.78**	**6.152**	10.28
		KHAMCD	100	100	-837.92	**-717.73**	-814.68	9.239	**7.39**
	20	KHA	100	100	-811.76	-546.68	-686.55	17.946	10.94
		KHAMC	100	100	**-837.96**	**-715.08**	**-815.69**	**9.6001**	10.70
		KHAMCD	100	100	-837.94	-599.54	-812.52	13.560	**7.75**
	30	KHA	100	100	-828.97	-583.27	-709.08	18.935	11.57
		KHAMC	100	100	-837.92	-712.30	-799.04	12.022	12.66
		KHAMCD	100	100	-837.91	-703.71	-809.94	10.752	7.53
		Fuzzy KHA [36]	25	200	6.38x10-4	-------	5.241x10-3	-------	-------

Function	D	Method	N	Imax	Best fitness	Worstfitness	Mean fitness	SD	CPU Time (sec)
		Choatic KHA [32]	------	500	-------	-------	-5905.55	2361.01	-------
		Choatic KHA [33]	25	200	1.874x10-4	-------	2.2151x10-2	-------	-------
f_7	2	KHA	100	100	9.3244x10-5	1.3229x10-1	1.8492x10-2	7.1446x10-3	11.72
		KHAMC	100	100	6.2953x10-8	2.2142x10-5	6.6838x10-6	1.7277x10-6	11.97
		KHAMCD	100	100	**1.0547x10-10**	**2.2662x10-5**	**2.4920x10-6**	**1.4490x10-6**	**8.88**
	20	KHA	100	100	8.0312x10-5	2.3803x10-2	5.2903x10-3	1.5889x10-3	12.00
		KHAMC	100	100	1.3340x10-7	4.9025x10-5	1.0330x10-5	3.1152x10-6	11.76
		KHAMCD	100	100	**2.9633x10-10**	**1.8687x10-5**	**2.7952x10-6**	**1.0101x10-6**	**8.28**
	30	KHA	100	100	2.8513x10-5	8.8107x10-2	9.8531x10-3	4.4336x10-3	11.49
		KHAMC	100	100	2.8175x10-7	7.2317x10-5	1.4779x10-5	4.9660x10-6	11.37
		KHAMCD	100	100	**6.5458x10-12**	**7.4766x10-6**	**1.3395x10-6**	**4.1764x10-7**	**7.96**
		Fuzzy KHA [36]	25	200	4.68x10-5	-------	0.000258	-------	-------
		Choatic KHA [32]	------	500	-------	-------	0.3541	0.318221	-------
		Choatic KHA [33]	25	200	0.0195	-------	0.24187	-------	-------
		KHAL [38]	10	10000	-------	-------	0.2504	0.2135	-------
f_8	2	KHA	100	100	**5.3259x10-6**	**5.5072x10-2**	**5.5912x10-3**	**2.7019x10-3**	11.77
		KHAMC	100	100	1.2777x10-2	6.3791x10-1	1.5062x10-1	3.0501x10-2	11.72
		KHAMCD	100	100	1.5709x10-2	5.9110x10-1	1.8952x10-1	3.0650x10-2	**8.17**
	20	KHA	100	100	**1.2544x10-4**	**9.0696x10-2**	**1.8495x10-2**	**5.44680x10-3**	11.85
		KHAMC	100	100	6.2359x10-3	3.2100x10-1	9.6901x10-2	1.7849x10-2	11.94
		KHAMCD	100	100	3.7283x10-3	5.8347x10-1	1.1992x10-1	2.8997x10-2	**8.71**
	30	KHA	100	100	**2.7725x10-5**	**1.9508x10-1**	**4.2240x10-2**	**1.19939x10-2**	11.76
		KHAMC	100	100	4.8975x10-3	2.8506x10-1	1.2771x10-1	1.7381x10-2	11.61
		KHAMCD	100	100	3.9030x10-3	2.3346x10-1	1.1508x10-1	1.8295x10-2	**8.26**
		Fuzzy KHA [36]	25	200	3.18330701	-------	7.807	-------	-------
		Choatic KHA [33]	25	200	3.983x10-5	-------	0.000165	-------	-------
		KHAL [38]	10	10000	-------	-------	0.0048	0.0108	-------

D: Dimension, SD: Standard Deviation





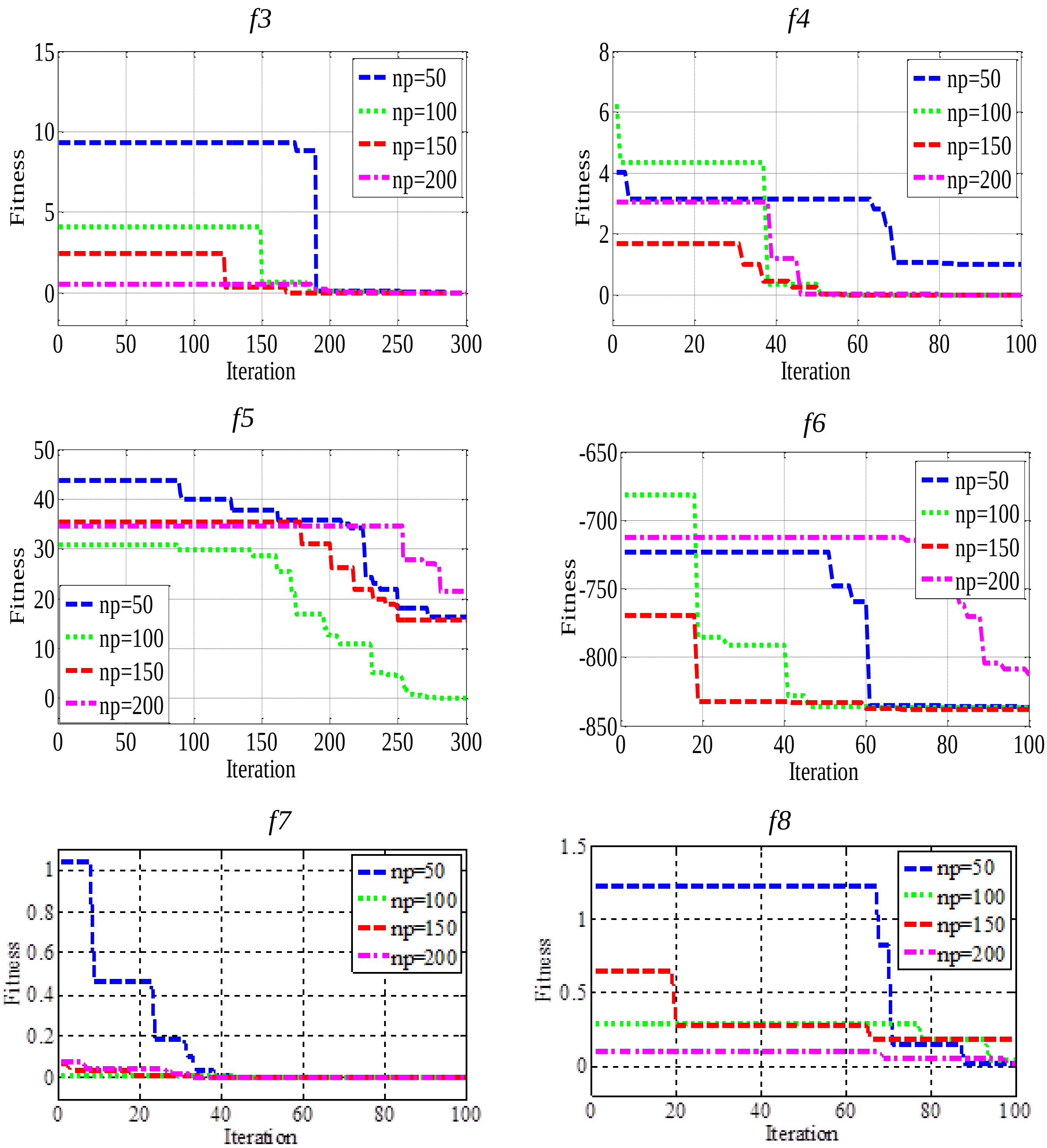


Fig.3. Convergence Characteristic of KHAMCD for different population on 20-D benchmark

C. Comparison of convergence characteristics

Convergence characteristic of KHAMCD algorithm are plotted with change in population in Fig 3 which shows that with increase in population the convergence improves. To make fair comparison between KHA, KHAMC and KHAMCD the convergence characteristics for different benchmark functions are compared in Fig 4, and the performance of KHAMCD is found to be better.

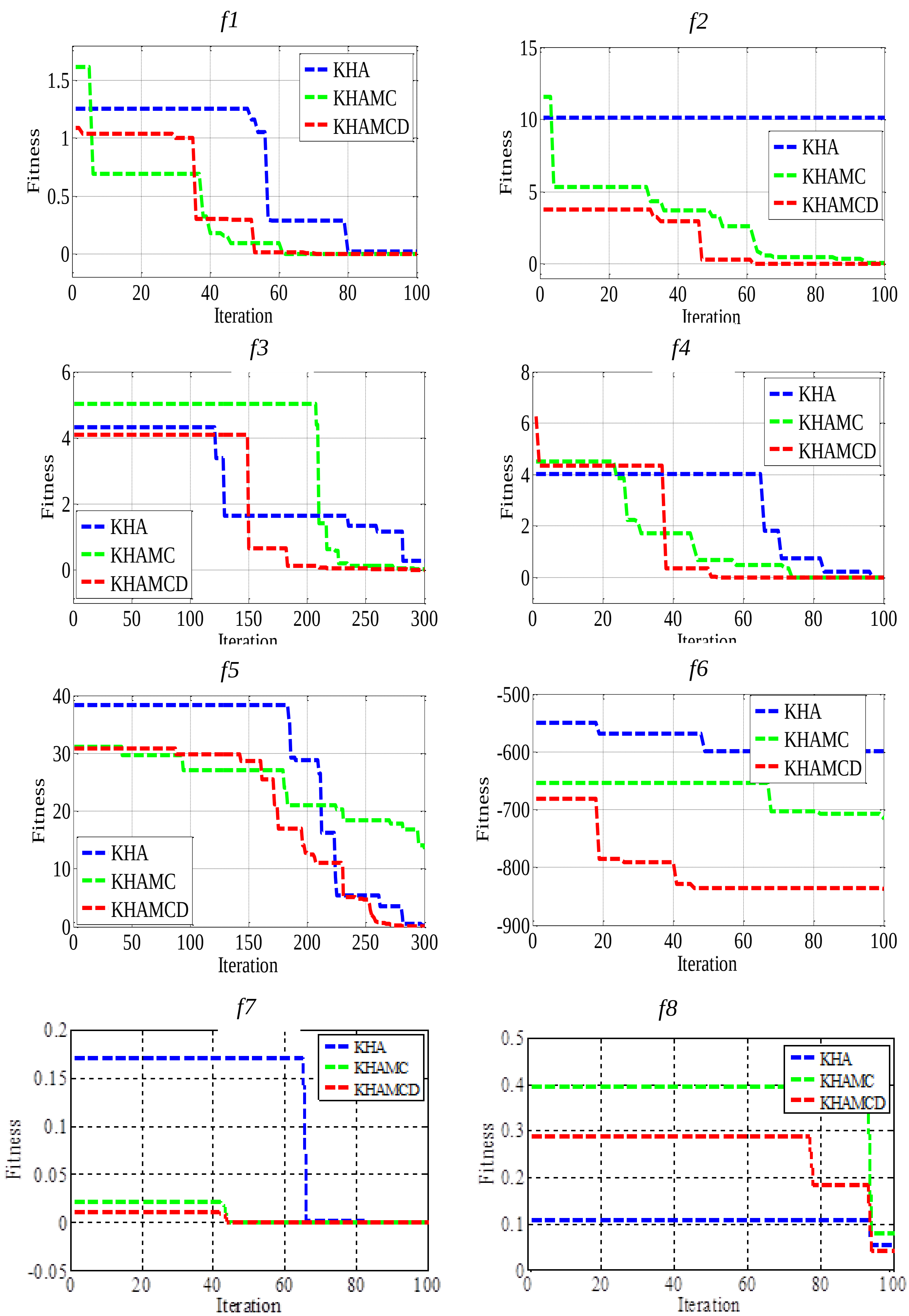


Fig.4. Comparison of convergence characteristics of variants of KHA

D. Consistency Analysis

As proposed KHAMCD uses random operators similar to other stochastic search optimization technique and hence in every trial the algorithm converge to slightly different value. Therefore, it is general practice to conduct various trials and statistical analysis is also carried out on benchmark functions as shown in Table 5. Also it is illustrated using Fig 5 with different population on 20-D. It is observed that population size of 100 good consistencies compared to other population for *f1 - f5, f8* whereas *f6, f7* have better consistency with population size of 150 and 200.

Table 5. Consistency Analysis of KHAMCD with different population size

Function *Name*	***N***	**Imax**	**Best fitness**	**Worst fitness**	***Mean***	***Standard Deviation***
f1	50	100	**5.2736x10-14**	1.4562x10-1	2.1843x10-2	1.1627x10-2
	100	100	8.6808x10-13	3.9258x10-4	2.4350x10-5	1.9234x10-2
	150	100	1.4977x10-13	1.5364x10-4	1.0477x10-5	7.6011x10-6
	200	100	1.7531x10-10	**1.0739x10-4**	**8.9068x10-6**	**5.3135x10-6**
f2	50	100	1.2343x10-6	4.0871x10-2	**3.2304x10-3**	2.2343x10-3
	100	100	**7.2152x10-7**	4.5232x10-2	4.8895x10-3	2.4332x10-3
	150	100	4.8540x10-6	4.7975x10-2	5.8461x10-3	2.4157x10-3
	200	100	3.2882x10-6	**3.2535x10-2**	1.0839x10-2	**2.4090x10-3**
f3	50	300	**7.8347x10-5**	9.6875x10-1	7.5608x10-2	4.7113x10-2
	100	300	3.1727x10-4	**1.8439x10-1**	**2.4747x10-2**	**1.0687x10-2**
	150	300	1.6369x10-4	7.3522x10-1	7.0285x10-2	3.9045x10-2
	200	300	1.1243x10-4	3.1155x10-1	2.9850x10-2	1.5157x10-2
f4	50	100	**1.2438x10-8**	9.9565x10-1	8.0639x10-2	5.3946x10-2
	100	100	2.3078x10-7	1.8638x10-3	4.6818x10-4	1.0556x10-4
	150	100	7.4842x10-7	1.6456x10-3	**2.8183x10-4**	7.2329x10-5
	200	100	1.8448x10-5	**1.4651x10-3**	2.8534x10-4	**6.6840x10-5**
f5	50	500	2.5094x10-2	**20.524**	**2.9311**	**1.0796**
	100	500	3.3115x10-3	31.275	6.3757	1.8344
	150	500	1.3246x10-2	20.726	8.3712	1.7670
	200	500	**2.9093x10-3**	25.036	8.4455	1.9047
f6	50	100	-837.94	-685.33	-780.43	13.311
	100	100	-837.92	-663.17	-789.62	13.822
	150	100	**-837.96**	**-719.13**	**-824.79**	**7.8827**
	200	100	-837.93	-717.05	-818.89	9.4561
f7	50	100	7.1146x10-11	5.8820x10-5	3.6337x10-6	2.8627x10-6
	100	100	1.0717x10-10	4.2097x10-5	3.2639x10-6	2.0344x10-6
	150	100	1.6174x10-08	1.4042x10-5	3.0890x10-6	9.3391x10-7
	200	100	**1.6004x10-12**	**5.7270x10-6**	**1.3783x10-6**	**3.8511x10-7**
f8	50	100	1.9340x10-2	1.1057	0.27688	0.057311
	100	100	**3.7283x10-3**	0.58347	0.11992	0.028997
	150	100	4.1531x10-3	0.24786	0.097353	0.016987
	200	100	9.8037x10-3	**0.19688**	**0.085857**	**0.015160**

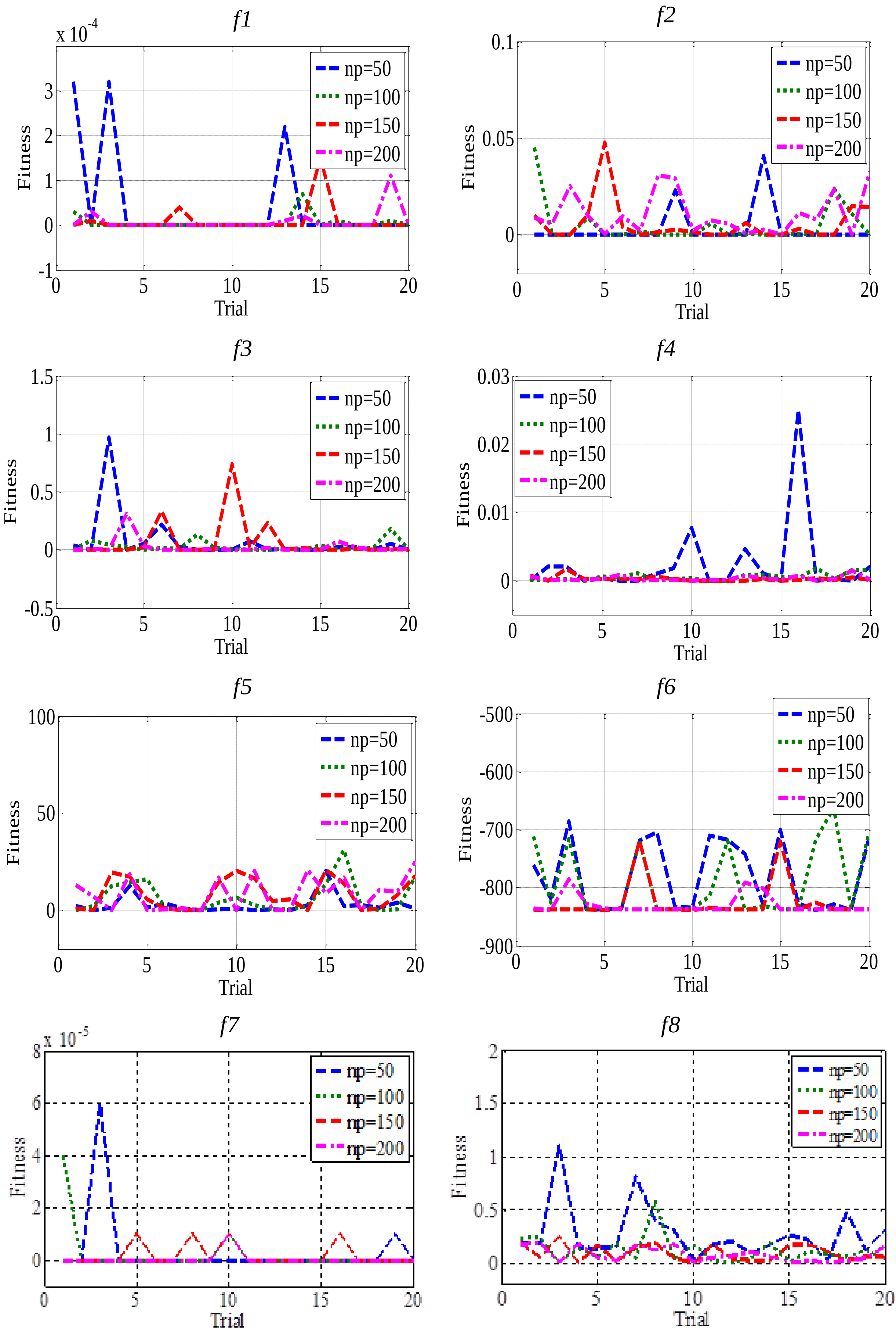


Fig.5. Consistency Analysis of KHAMCD on 20-D benchmark

IV. ECONOMIC LOAD DISPATCH PROBLEM

In this section KHAMCD algorithm is used to optimize practical Economic Load Dispatch (ELD) problem. ELD is key issue related with power system operation and control with goal is to find out most reliable, efficient and low cost operation of power system that can capable to match required power demand by proper dispatch of output from committed generators. ELD is complex optimization problem with main objective is to minimize the cost function and has to satisfy the operating constraints too. These types of problem have many minima and hence classical method unable to provide global best solution. On the other hand population based stochastic search NI method often provides near global solution is a better choice for solution of these types of problem.

Various optimization techniques as lamda iteration [41], quadratic programming and GAMS [52], differential evolution(DE)[43], teaching learning based optimization(TLBO)[44], Chemical Reaction Optimization (CRO) [45], krill herd algorithm(KHA) [46,53] invasive weed optimization(IWO) [47], gravitational search (GSA)[48], flower pollination algorithm(FPA) [49], Artificial Bee Colony(ABC) [50], rooted tree optimization(RTO) [51] and hybrid DE with particle swarm optimization (PSO) [52] are successfully applied for solution of ELD problem.A comprehensive review of NI techniques for solution ELD problem is presented in [40]

To validate the performance of proposed KHAMCD it is tested on two standards complex constraint comparative medium and large scale ELD problem as below.

A. ELD formulation as cost function

The objective function corresponding to the power generation cost can be approximated as quadratic function of the active power outputs of committed the generating units. Symbolically, it is represented as:

$$Minimize \quad F_T = \sum_{i=1}^{N} f_i(P_i) \tag{13}$$

Where $f_i(P_i) = a_i P_i^2 + b_i P_i + C_i$ (14)
i=1,2,3,………N

a_i, b_i and c_i represents its cost coefficients. Expression for cost function (14) corresponding to i^{th} generating unit, P_i is the real power output (MW) and N is the number of online generator used for power dispatched. The cost function with valve point loading effect is computed as[48,49:

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left\{ f_i \times \left(P_i^{\min} - P_i \right) \right\} \right| \tag{15}$$

Where e_i and f_i indicating the valve point effect of i^{th} generator.

Subjected to constrains as

1) Power balance constraint

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{16}$$

The transmission losses occurring in the system can be expressed using B-loss coefficients as [41]:

$$P_L = \sum_{i=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} P_i B_{i0} + B_{00} \tag{17}$$

2) Operating limit constraint

$$P_i^{\min} \le P_i \le P_i^{\min}, \qquad \text{where i= 1,2,….N} \tag{18}$$

The generated output of i^{th} generator should lie between specified lower and upper limit.

3) Constraints due to prohibited operating zones

The prohibited operating zones (POZ) are the certain range of output power of a generator, in that rage of operation unnecessary vibration in turbine shaft takes place which may damage the shaft and bearing and hence operation is avoided in such regions. POZ makes the objective function discontinuous, therefore feasible operating zones of power generating unit can be depicted as:

$$\left\{ \begin{array}{l} P_i^{\min} \le P_i^t \le \underline{P}_i^1 \\ P_i^{-x-1} \le P_i^t \le \underline{P}_i^x \qquad x = 2,3.......nz, \\ P_{Gi}^{-nz} \le P_{Gi} \le P_{Gi}^{\max} \end{array} \right\} \tag{19}$$

Where, $\underline{P}_i^x and \overline{P}_i^x$ are the lower and upper operating limits of the x^{th} prohibited operation zone for i^{th} power generating unit.

B. Results and discussion

The applicability and viability of the aforementioned proposed KHAMCD algorithm for practical applications has been tested on two different test cases of ELD problem with population size (N) set at 100 and other parameter are similar as in section III.A.

1) Fifteen unit system with POZ and loss

The system contains fifteen thermal generating units. Four power generating unit as 2, 5, 6 and 12 has prohibited operating zones. The fuel cost coefficient data and transmission line loss coefficient are adopted as per [46]. The total load demand on the system is 2630 MW. The optimum generation schedule obtained by proposed algorithm is presented in Table 6 and the statistical comparison of result is made in Table 7 respectively. The optimum generation cost obtained by KHAMCD 32548.0031$/hr which is found to be slightly inferior to KH IV [46], but considering overall statistical evaluation, the performance of KHAMCD is found to be better and consistent. The convergence characteristic for this test case is plotted in Fig.6.

It can be seen from results that the KHAMCD technique provides better results while satisfying the associated operating constraints.

Table 6. Optimum generation of KHAMCD for Test Case 1

Unit	KH IV [46]	KHAMCD	Unit	KH IV [46]	KHAMCD
P1	455	455	*P10*	31.2698	35.6215
P2	455	455	*P11*	76.7013	74.3593
P3	130	130	*P12*	80	80
P4	130	130	*P13*	25	25
P5	233.8017	231.7891	*P14*	15	15
P6	460	460	*P15*	15	15
P7	465	465	$\sum P_i$ (MW)	2656.7728	2656.7699
P8	60	60	Ploss (MW)	26.7673	26.7699
P9	25	25	Total cost ($/h)	32547.3700	32548.0031

Table 7. Statistical results of KHAMCD for Test Case 1

Method	Min Cost($/hr)	Mean Cost($/hr)	Max Cost($/hr)	S.D	CPU time(sec)
KH IV[46]	32547.3700	32548.1348	32548.9326	NA	NA
DEPSO[54]	32588.8100	32588.9900	32591.4900	4.0200	1.9600
DPD [54]	32548.5857	32556.6793	32564.4051	2.0956	1.9800
KHAMCD	32548.0031	32548.1020	32548.354	0.1570	1.870

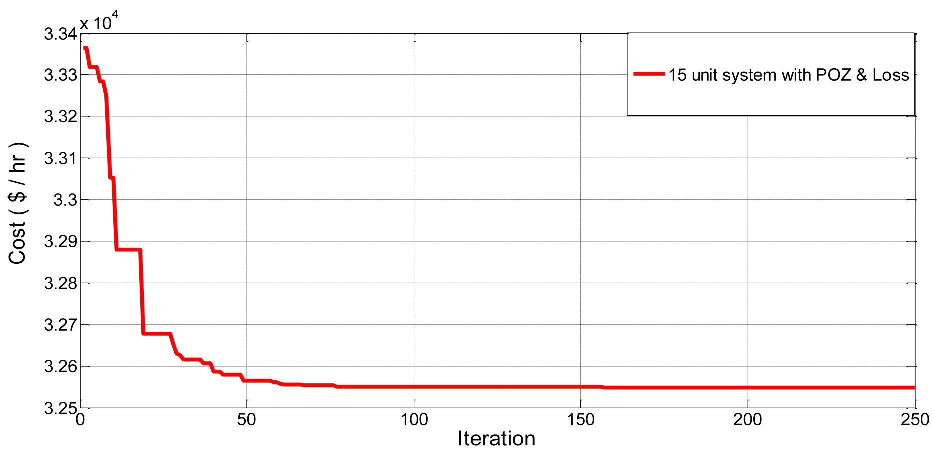


Fig.6. Convergence characteristic of KHAMCD for Test case 1

2) Forty unit nonconvex system

To examine the superior quality of solution and robustness of KHAMCD algorithm a more realistic test case with valve point loading effect and transmission line losses is included here. The fuel cost coefficient data and transmission line loss coefficients are adopted from [47]. The power demand for system is 10500MW. Solution in terms of optimum generation schedule obtained by simulation is presented in Table 7I. The statistical performance over twenty trials is tabulated in Table 9. The best operating cost achieved by the KHAMCD method is 136446.4053$/hr .The comparison of result has been made with hybrid genetic algorithm with ant colony optimization (GAAPI) [42], shuffled differential evolution (SDE) [43], teaching learning based optimization (TLBO) [44], oppositional real coded chemical reaction optimization (ORCCRO) [45] , krill herd algorithm (KHA) [46], oppositional invasive weed optimization (OIWO) [47] and most recently reported Opposition-based krill herd algorithm (OKHA)[53], hybrid PSO DE approach[54]. Here it can be observed that proposed method KHAMCD is able to achieve cheapest generation cost as compared to other reported methods. Smooth and stable convergence characteristic of this system obtained by KHAMCD algorithm for power demand of 10500MW with transmission loss is shown in Fig 7.

Table 8. Optimum Generation of KHAMCD for Test Case 2

unit	KHAMCD	KH IV[46]	OIWO[47]	SDE [43]	unit	KHAMCD	KH IV[46]	OIWO[47]	SDE [43]
P1	114	114	113.9908	110.06	P21	523.2794	524.4678	549.9412	544.81
P2	114	114	114.0000	112.41	P22	535.9596	535.5799	549.9999	550
P3	120	120	119.9977	120	P23	523.2794	523.3795	523.2804	550
P4	179.7331	190	182.5131	188.72	P24	523.2794	523.15527	523.3213	528.16
P5	87.8005	88.5944	88.4227	85.91	P25	523.2794	524.1916	523.5804	524.16
P6	140	105.5166	140.0000	140	P26	523.2794	523.5453	523.5847	539.10
P7	300	300	299.9999	250.19	P27	10	10.1245	10.0086	10
P8	300	300	292.0654	290.68	P28	10	10.1815	10.0068	10.37
P9	300	300	299.8817	300	P29	10	10.0229	10.0123	10
P10	279.5997	280.6777	279.7073	282.01	P30	87.7999	87.8154	87.8664	96.10
P11	168.7998	243.5399	168.8149	180.82	P31	190	190	190.0000	185.33
P12	94	168.8017	94.0000	168.74	P32	190	190	189.9983	189.54
P13	484.0392	484.1198	484.0758	469.96	P33	190	190	190.0000	189.96
P14	484.0392	484.1662	484.0477	484.17	P34	200	200	199.9940	199.90
P15	484.0392	485.2375	484.0396	487.73	P35	200	164.9199	200.0000	196.25
P16	484.0392	485.0698	484.0886	482.30	P36	164.7999	164.9787	164.8283	185.85
P17	489.2794	489.4539	489.2813	499.64	P37	110	110	110.0000	109.72
P18	489.2794	489.3035	489.2966	411.32	P38	110	110	109.9940	110
P19	511.2794	510.7127	511.3219	510.47	P39	110	110	110.0000	95.71
P20	550	511.3040	511.3350	542.04	P40	550	512.0677	550.0000	532.43
Total cost ($/h)						136446.4053	136670.3701	136,452.677	138,157.46
P loss (MW)						958.8845	978.9251	957.2965	974.43

Table 9. Statistical results of KHAMCD for Test Case 2

Method	Min Cost($/hr)	Mean Cost($/hr)	Max Cost($/hr)	S.D	CPU time(sec)
GAAPI [42]	139864.96	NA	NA	NA	NA
SDE [43]	138,157.46	NA	NA	NA	NA
ORCCRO[45]	136,855.19	136,855.19	136,855.19	NA	14
TLBO[44]	137814.17	NA	NA	-------	-------
QOTLBO[44]	137329.86	NA	NA	-------	-------
OIWO [47]	136,452.68	136,452.68	136,452.68	NA	10.7
KHA-IV[46]	136670.3701	136671.2293	136671.8648	NA	NA
OKHA[53]	136,575.97	136,576.15	136,576.64	NA	NA
KHAMCD	136446.4053	136454.8868	136474.1348	11.0218	9.964

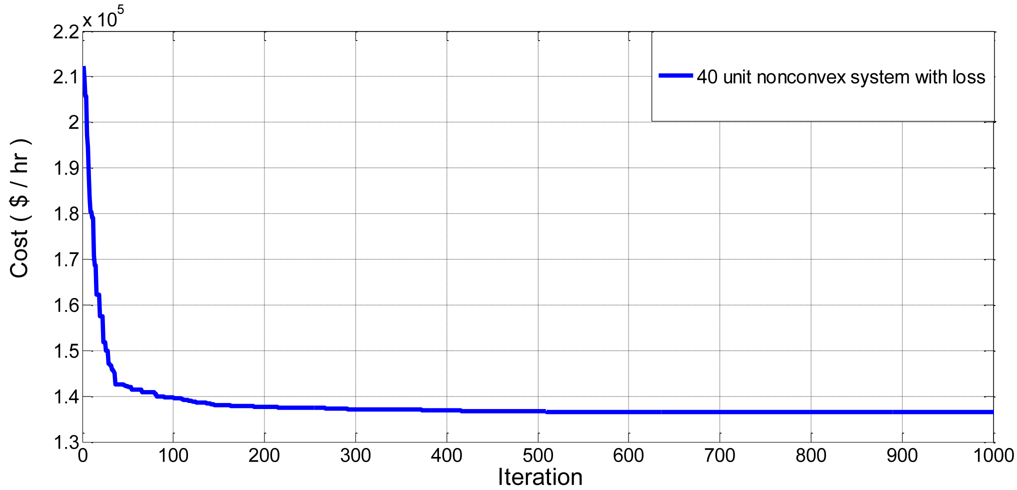


Fig.7. Convergence characteristic of KHAMCD for Test case 2

V. CONCLUSION

Krill herd algorithm (KHA) belongs to the family of nature inspired stochastic search algorithms. To improve global search capability and convergence characteristics, the basic KHA has been improved by (i) adding crossover and mutation operators (KHAMC) and (ii) by including neighborhood distance concept (KHAMCD). The modified versions of KHA are employed to solve eight unimodal/multimodal benchmark functions as well as two non-smooth and non-convex ELD problems of power system. The basis KHA was tested on different mathematical benchmark problems and its performance was found to be satisfactory in terms of convergence and consistency. The performance of the algorithm was found to be improved in terms of solution quality by using mutation and crossover operators. When neighborhood distance concept was added, for the same accuracy, the computational time was reduced to around 26 to 30% and exploration and exploitation level of krill herd is balanced properly. Various trials were conducted with different initial populations and it was found that every time KHAMCD produced accurate results within tolerance band. As compared to recently reported results in literature, the performance of KHAMCD is found to better in terms of solution quality. From this comparative analysis, it can be concluded that the proposed methodology can effectively be used to solve smooth as well as non-smooth constrained optimization problems.

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Authors' Profiles

Prasun K. Agrawal obtained his B.Tech degree in Electrical and Electronics Engineering from Integral University, Lucknow, (India) in 2013. He is currently pursuing his M.E degree in Electrical Engineering (Industrial System and Drives), from M.I.T.S, Gwalior, (India). His areas of interest are Optimal Power Flow, evolutionary computing and artificial intelligence applications to Power System.

Hari Mohan Dubey obtained his M.E. degree in Electrical Engineering from Madhav Institute of Technology & Science Gwalior (India) in 2002. He is currently working as Assistant Professor in Department of Electrical Engineering, M.I.T.S., Gwalior, (India). His areas of research are Computational intelligence algorithm and their applications to power system.

Manjaree Pandit obtained her M. Tech degree in Electrical Engineering from Maulana Azad College of Technology, Bhopal, (India) in 1989 and Ph.D. degree in 2001. She is currently working as Professor in Department of Electrical Engineering, M.I.T.S., Gwalior, (India). Her areas of interest are Power System Security Analysis, Optimization using soft computing/ evolutionary methods, ANN and Fuzzy neural applications to Power System.

How to cite this paper: Prasun Kumar Agrawal, Manjaree Pandit, Hari Mohan Dubey, "Improved Krill Herd Algorithm with Neighborhood Distance Concept for Optimization", International Journal of Intelligent Systems and Applications (IJISA), Vol.8, No.11, pp.34-50, 2016. DOI: 10.5815/ijisa.2016.11.05

